The Reluctant Analyst *

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Abstract

We estimate the dynamics of recommendations by financial analysts, uncovering the determinants of inertia in their recommendations. We provide overwhelming evidence that analysts revise recommendations reluctantly, introducing frictions to avoid frequent revisions. More generally, we characterize the sources underlying the infrequent revisions that analysts make. Publicly-available data matter far less for explaining recommendation dynamics than do the recommendation frictions and the long-lived information that analysts acquire that the econometrician does not observe. Estimates suggest that analysts structure recommendations strategically to generate profitable order flow from retail traders. We provide extensive evidence that our model describes how investors believe analysts make recommendations, and that investors value private information revealed by analysts' recommendations.

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1 Introduction

One of the most important services that financial analysts provide is to make recommendations to retail and institutional customers about which stocks to purchase, and which ones to sell. Brokerage houses want to employ financial analysts who provide recommendations on which investors can profit, thereby generating profitable trading activity for the brokerage house. Many researchers (e.g., Womack, 1996; Francis and Soffer, 1997; Barber et al., 2001 and 2006; Jegadeesh et al., 2004; Ivković and Jegadeesh, 2004; Howe et al., 2009; and Bradley et al., 2014) have documented the profitability and informativeness of various measures of recommendations and recommendation changes.

In this line, one can contemplate an "idealized" financial analyst who first gathers and evaluates information from public and private sources about a set of companies to form assessments about their values, and then compares his value assessment with the stock's price, issuing recommendations to his investor audience on that basis. Thus, an idealized analyst employing a five-tier rating system would issue "Strong Buy" recommendations for the most under-valued stocks, whose value-price differentials, $\frac{V-P}{P}$, exceeded a high critical cutoff, μ_5. The analyst would establish progressively lower cutoffs, μ_4, μ_3 and μ_2, that determine "Buy", "Hold", "Sell" and "Strong Sell" recommendations, so that, for example, the analyst would issue Buy recommendations for value-price differentials between μ_5 and μ_4, and strongly advise customers to sell stocks with the worst value-price differentials below μ_2.

Analysts do not form recommendations in this way. To understand why, observe that sometimes a stock's value-price differential will be close to a cutoff, in which case slight fluctuations in price relative to value lead to repeated recommendation revisions. In practice, analysts infrequently revise recommendations—customers would question the ability of an analyst who repeatedly revised recommendations on which they based investments.

We develop and estimate a model of a "reluctant" financial analyst. The analyst assesses value just like an idealized analyst, and when initiating coverage, he makes an initial recommendation on the same basis. However, the analyst only downgrades a recommendation if the value-price differential falls far enough below the critical cutoff, and only upgrades a recommendation if the value-price differential rises far enough above the cutoff. Thus, a reluctant analyst downgrades a recommendation from a Buy only if a stock's value-price differential falls below $\mu_4 - \delta_{4\downarrow}$ instead of μ_4, and he upgrades from a hold only if the differential rises above $\mu_4 + \delta_{4\uparrow}$ instead of μ_4, where $\delta_{4\downarrow}$ and $\delta_{4\uparrow}$ are stickiness parameters that measure an analyst's strategic "reluctance" to revise recommendations.[1]

The contributions of our paper are first to identify the drivers and determinants of stickiness in analyst recommendations. We distinguish the relative importance of recommendation revision frictions, persistent analyst information and public information available to an econometrician for explaining the dynamics of analyst recommendations. In turn, these drivers provide insights into the strategic considerations and information of analysts. We uncover how incorporating strategic behavior and analyst information alters our understanding of how various public information characteristics of a firm (e.g., size, past performance) enter an analyst's assessment of firm value. We show how our model informs about the returns of firms following recommendation revisions inside and out of earnings announcement and guidance windows. Finally, we show that our model provides a measure of the "surprise" associated with a recommendation revision or initiation that explains the magnitudes of returns.

There are many different sources of stickiness in recommendations, and the econometric model must account for each of them to avoid biasing estimates that lead to mistaken inferences about their relative importance. One source of stickiness is simply that much of the public information that analysts receive arrives in lumps. Concretely, earnings announcements arrive quarterly, and earnings guidance is given sparingly. An unsurprising consequence, for example, is that recommendation revisions are more likely inside announcement and guidance windows, generating "stickiness" outside these windows.

A second source of stickiness is the information that analysts uncover to which an econometrician is not privy. This information could reflect an analyst's assessments based on *repeated* private interactions with firm personnel.[2] Alternatively, the information need not be "private", just unobserved by the econometrician, and hence not in his model of valuation even when the information enters price.[3] The valuation consequences of such information persist—if an analyst has favorable information that the econometrician lacks, some of the information likely remains months later, positively affecting future recommendations.

[1]See Section 2.1 for extensive motivation of these stickiness parameters.

[2]According to a survey conducted by Brown, Call, Clement, and Sharp (2015, JAR), analysts' private communication with management is the *most* useful input to their decision process when forming earnings forecasts and stock recommendations; and "over half of the analysts we survey report that they have direct contact with the CEO or CFO of the typical company they follow *five or more times a year*."

[3]For example, the public information could be the quality of the CEO, which is obviously persistent; it could be approval of a drug by the FDA, which will enter share price both now and into the future (but possibly not near term earnings), and the value of this approval will persist; it could be the near term entry or exit of rivals; the value of new patents (or future expiration of old ones), etc. Quite generally, any information that enters distant future revenues will typically be both quite persistent, known to the analyst and the market, but not fully captured by a set of control variables.

A third source of stickiness is the strategic choices by analysts. Analysts can reduce the likelihood of revising recommendation i by increasing its bin size, $\mu_{i+1} - \mu_i$, or by increasing the recommendation frictions $\delta_{i+1\uparrow}$ and $\delta_{i\downarrow}$ into higher and lower recommendations. Moreover, an analyst can reduce the frequency of recommendation revisions not only with symmetric frictions, but also with asymmetric ones, where say the friction from buy to hold is large, but that from hold to buy is small. Analysts have flexibility in how they tailor frictions to limit recommendation revisions, and choices may hinge on the recommendation itself.

We test the model using analyst recommendations from the post Reg-FD,[4] post Global Analyst Research Settlement period, where analysts could issue negative sell recommendations without fear of losing access to company information sources (Chen and Matsumoto, 2006; Bradshaw, 2009). We estimate separate models for brokerage houses that employ three-tier rating systems and those that use the traditional five-tier rating system,[5] and for various subsamples (e.g., of larger brokerages).

The publicly-available characteristics that we find enter an analyst's assessment of value positively tend to be consistent with the findings of others (e.g., Conrad et al., 2006). An important exception is that, contrary to existing findings, once one controls for the reluctant analyst's strategic behavior and private information, measures of *past* firm performance (lagged returns) cease to positively affect assessments. That is, the idealized analyst model provides a misleading indication of the impacts of past firm performance on recommendations.

What is fundamentally more important than these results is the fact that readily-available public information sources matter *far less* for explaining the dynamics of analyst recommendations than do recommendation frictions and persistent analyst information. Highlighting this, the Bayes factor (the ratio of the marginal likelihoods of the alternative and null models) is an astonishing $exp(81660)$ for (a) the null model of an idealized analyst that includes all standard public information sources of valuation, but no persistent analyst information and (b) a barebones alternative model of a reluctant analyst that includes **no** public information components of valuation, and only two recommendation revision frictions, one for upgrades and one for downgrades, plus persistent analyst information.[6]

[4] Reg FD was designed to curb the practice of selective disclosure of material nonpublic information. Reg FD eliminated incentives of analysts to issue favorable recommendations in order to curry favor with firms and hence retain access to nonpublic information. Reg FD came into effect in August 2000.

[5] Kadan et al. (2009) find that following the Global Analyst Research Settlement and related regulations on sell-side research in 2002, many brokerage houses, especially those affiliated with investment banks, switched from a five-tier rating system to a three-tier system; and subsequently more have switched.

[6] The Bayes factor is employed to assess the goodness of model fit in Bayesian estimation. A Bayes factor of $2\log(B)$ that exceeds 10 ($\approx B > 150$) represents decisive evidence in favor of the alternative

The result that persistent analyst information matters more for recommendations than does the information available to the econometrician is important. It suggests that most of the econometrician's information is already incorporated into prices, and hence has only secondary impacts on recommendations. We find that about one-third of the valuation consequences of an analyst's information persists to the next month.

The recommendation revision frictions that analysts introduce are as important for model fit as their information. Failing to account for these frictions biases up the estimate of the persistence in analyst information, almost *tripling* the estimate. We find that analysts tailor revision frictions asymmetrically, depending on the recommendation. Analysts introduce much smaller frictions "out" of hold recommendations than "into" hold recommendations. This suggests that analysts do not like to maintain hold recommendations, perhaps because they generate less trading volume for a brokerage house. For analysts using a five-tier rating system, we find that sell and buy recommendation bins are small relative to the frictions from strong sell to sell and strong buy to buy, so that most revisions are to hold. This, too, suggests strategic considerations: revisions from strong buy to buy that maintain a positive assessment or from strong sell to sell that maintain a negative assessment may not be enough to induce customers to unwind positions, but larger revisions to hold may do so.

We find that analysts who use the same (e.g., three-tier) recommendation rating system are well-described by a common model of recommendation bins and frictions, where sources of heterogeneity (firm and analyst attributes) only enter an analyst's valuation assessment. To show this, we estimate our model on subsamples where one might posit that analyst recommendations might vary—over time, by brokerage size or analyst experience or number of analysts following a firm. Estimates across subsamples are remarkably robust. As a final validation test, we investigate whether some of our stickiness findings might proxy for analysts' imperfect and delayed reaction to new information (Raedy et al. 2006): we estimate a model in which analysts may process some new information with a lag. Estimates suggest slightly delayed incorporation of information, but over 90% is processed immediately. Moreover, allowing for delayed reaction to information *raises* the estimate of information persistence by one-third and has modest impacts on recommendation friction estimates.

Having validated the model structure, we investigate its implications. We predict and verify that recommendation revisions made outside earnings announcement or guidance win-

model against the null (Kass and Raftery, 1995). A factor that exceeds $1,000$ provides conclusive support for forensic evidence in a criminal trial (Evett, 1991). See Appendix A for details.

dows should take longer to return to the original recommendation, reflecting that information arrival is smoother outside these windows. In fact, the mean duration of a recommendation revision is 6-8 days longer if issued in a three-day window (on and after) of an earnings announcement or guidance date, than if issued outside these windows. We also predict and verify that recommendation revisions made inside these windows should have greater impacts on stock prices than revisions made at other times. Finally, we exploit the fact that the discontinuity in valuation assessment *only* occurs for revisions and *not* new recommendations. A difference-in-difference analysis of revisions vs. new recommendations inside and out of announcement and guidance windows shows that our model can reconcile the different market responses to new and revised recommendations made inside vs. out of these windows.

We conclude by exploiting the fact that our model provides a measure of the "surprise" associated with a recommendation revision or initiation. For example, if the current estimate of an analyst's stock valuation given *publicly-available* information is below an upgrade revision cutoff, the market should be more surprised by an upgrade than if the estimated valuation suggests that the revision should already have been made. That is, the market should be more surprised by an upgrade to a buy if a stock's public information value suggests a hold than if it already suggests a buy. Thus, we predict a difference in the (appropriately signed) CARs following revisions in these two scenarios. So, too, when an analyst initiates coverage, the market response to a buy recommendation should be smaller if the current assessment of value given public information suggests a buy recommendation than if it indicates a hold.

We find both of these CAR relationships in the data. They indicate that (a) investors believe analysts make recommendations along the lines of our model, and (b) the market values the information that analysts acquire that the econometrician does not have. They also imply that the impacts of any unmodeled behavior-distorting incentives on recommendation formation, which just add noise, are modest enough that we still uncover these CAR relationships.

The paper is organized as follows. We next review the related literature. Section 2 develops our model of the analyst recommendation process and provides an overview of model identification and estimation. Section 3 details our data. Section 4 presents our findings. Section 5 concludes. Appendix A includes more details on our estimation procedure and the assessment of goodness-of-fit. Appendix B defines variables used in our analysis.

1.1 Related literature

There is a large literature in accounting and finance on analyst recommendations. Our paper is the first to directly model revision stickiness and to explore its strategic design. It differs sharply from the existing literature in its focus and methodology. Methodologically, most existing analyses employ combinations of the following methods:

- Descriptive statistical relationships between analyst and firm characteristics and recommendations, such as sample means, correlations, or quintiles (e.g., Jegadeesh et al. (2004), Ivković and Jegadeesh (2004) and Boni and Womack (2006)).
- Regressions of recommendations on returns or vice versa, and/or regressions based on recommendation changes.[7]
- Investment strategies based on portfolio construction using recommendation information, showing that they have positive value (Barber et al. (2001), Jegadeesh et al. (2004), Jegadeesh and Kim (2010), Boni and Womack (2006)).

The impact of analysts' conflicts of interest on recommendations have also been closely examined. Ljungqvist et al. (2006) use a limited dependent variable model to examine securities underwriting mandates, showing that investment banking relationships lead to more favorable recommendations. Michaely and Womack (1999) find that lead underwriters issue more favorable recommendations. Lin and McNichols (1998) report that affiliated analysts issue more favorable recommendations.

Conrad et al (2006) are the first to recognize the impact of outstanding recommendations on later revisions in an ordered probit framework. We next relate our paper to theirs in detail and further motivate our study.

[7] Stickel (1995) and Womack (1996) show that upgrades are associated with positive announcement returns; Barber et al. (2001, 2006) find that absent transactions costs, investors could profit from information in recommendations; Jegadeesh et al. (2004) and Jegadeesh and Kim (2006) find that recommendations predict future returns, and that analysts tend to issue more favorable recommendations for stocks, finding that analysts tend to issue more favorable recommendations for stocks with positive momentum and higher trading volume, and that analysts fail to respond quickly to negative signals by downgrading stocks; Ivkovic and Jegadeesh (2004) find a sharp increase in the information content of recommendation upgrades (but not downgrades) before earnings announcements; Boni and Womack (2006) find that recommendation information is valuable for identifying short-term, within-industry mispricing; and Loh and Stulz (2011) look at abnormal returns around recommendation changes, and study when such changes are influential. Bagnoli et al. (2009) find market sentiment helps to explain bias in analyst recommendations.

Further motivation and the relationship with Conrad et al. (2006). The ordered probit model, in which recommendations are regressed on variables capturing stock value via a probit link function estimates a model of an idealized analyst in which the econometrician sees the analyst's valuation information. However, due to the reluctance of analysts to revise recommendations, if stickiness is not directly modeled, cutoff estimates have to absorb the friction parameters and will vary with the outstanding recommendation—the cutoff between a Buy and a Hold would be higher if estimated on the basis of an outstanding Hold than if based on an outstanding Buy; and the cutoff would be "inbetween" if estimated using initial recommendations.

Recognizing this and assuming away persistence in analyst information, Conrad et al. divide the data according to the outstanding recommendation and *separately* estimate a probit model via MLE on each sub-sample. They then weight parameter estimates β by the number of observations in each recommendation level, and calculate transition probabilities based on these estimates. They find that analysts are more likely to revise recommendations after negative price shocks than positive ones.

There are econometric issues with this approach. First, averaging over sub-sample estimates in a non-linear model does not deliver correct inferences on cutoffs, reflecting that the partial effect of changes in a regressor is a function of both β and μ.[8] In turn, estimates of transition probabilities are biased as they depend on the correct estimation of cutoffs. Second, because their cutoff estimates reflect a mixture of the true cutoff and stickiness parameters, one cannot discern the economic and statistical significance of their estimates of β. Third, serial correlation in analyst information ($\rho \neq 0$) introduces additional issues. Due to the correlation of some regressors with the residual term, estimates are further distorted. Finally and more generally, regardless of whether an ordered probit model is based on the full sample or is conditioned on the outstanding rating, it does not incorporate the intertemporal stickiness in recommendations and high information persistence found in the data, and we document the large biases that result.

Most importantly, their research focus is very different. Conrad et al. focus on the asymmetric impact of lumpy informational events for recommendation revisions, and not the sources and consequences of recommendation stickiness.[9] We show that lumpy public

[8]For instance, the marginal impact of a continuous regressor x_1 on the probability of issuing a Buy rating is $\partial \Pr(R=2|X)/\partial x_1 = \beta_1 \times [\phi(\mu_1 - X\beta) - \phi(\mu_2 - X\beta)]$, where $\phi(\cdot)$ is the pdf of a standard normal.

[9]Conrad et al. do not even report the recommendation cutoff parameter estimates, much less how they vary with the outstanding recommendation.

information is a minor source of stickiness in recommendations. The inability of public information alone to explain recommendations manifests itself in the low pseudo-R^2's (well below 5%) that Conrad et al. (2006) and Ljungqvist et al. (2007) find.[10]

Quite differently, our paper seeks to characterize the dynamics of analyst decision-making and recommendation formation, jointly accounting not only for the public information available to the econometrician, but also the persistent information of analysts and the recommendation revision frictions that they strategically introduce. Our joint estimation yields a valid statistical inference that facilitates formal hypothesis testing. We show that revision frictions and persistent analyst information are the primary drivers for explaining analyst recommendations and the stickiness in recommendations. We find that heterogeneity between analysts is well-captured by heterogeneity in their models of valuation assessment, together with a homogeneous model of recommendation formation. We identify how analysts design recommendation frictions asymmetrically to generate trade from investors, and we show that analysts quickly incorporate new information into their recommendations. Finally, our model provides a theoretical lens through which to understand the different impacts of recommendation revisions made inside versus outside earnings announcement windows, to incorporate analyst underreaction, and to explain recommendation "surprise".

2 The model and its estimation

This section develops our model of the analyst recommendation process in the context of an analyst who employs a five-tier rating system. The model of an analyst who employs a three-tier rating system is similar.

2.1 The dynamic setup

If recommendations reflect buying opportunities, then they should reflect the difference between an analyst's assessment of a stock's valuation and its share price. This valuation assessment may reflect expected discounted earnings, or technical considerations that reflect market mispricing; and it may be prospective (e.g., an analyst's forecast of firm value in a year's time). Moreover, the notion of value is from an *analyst's* perspective: in addition to standard valuation fundamentals, attributes that appeal to an analyst's retail investor

[10]The analogous regression in which, as in Loh and Stulz (2011), *changes in recommendation* are regressed on the controls variables using an ordered probit, fits the data even less well with an adjusted-R^2 of 0.33%.

audience (e.g., small, growth, glamor stocks), or attributes such as underwriting business that only the analyst cares about, may enter an analyst's assessment of value.

Let V^*_{ijt} be analyst i's per share valuation of stock j at time t, which equals the per-share difference between the analyst's assessment of "value V_{ijt}" and price (P_{jt}):

$$V^*_{ijt} = \frac{V_{ijt} - P_{jt}}{P_{jt}}.$$

We assume that V^*_{ijt} is determined by a large set of explanatory variables (see Appendix B for variable descriptions) and analyst i's own information. Letting X_{ijt} be the per-share analogue of these variables, we write analyst i's per-share valuation model as:

$$V^*_{ijt} = X'_{ijt}\beta + u_{ijt}. \tag{1}$$

The unobserved residual terms u_{ijt} capture information that the analyst has, to which the econometrician is not privy. As the introduction highlights, both omitted public information and an analyst's repeated interaction with management tend to cause serial correlation: we must allow for persistence in u_{ijt} to capture the fact that the valuation consequences of this information will last for some time. Accordingly, we assume that u_{ijt} evolves according to an AR(1) process:

$$u_{ijt} = \rho u_{ij,t-1} + \varepsilon_{ijt}, \tag{2}$$

where ε_{ijt} are i.i.d. $\mathrm{N}(0, \sigma^2)$ and ρ measures the persistence in the valuation consequences of the analyst's information. For identification purposes, we normalize $\sigma^2 = 1$.[11]

As our introduction highlights, analyst i's recommendation for stock j at date t, R_{ijt}, is a function of both his valuation V^*_{ijt} *and* his outstanding recommendation. Thus, the model that determines an analyst's recommendation when he initiates coverage is *not* the same as the one that he uses to determine subsequent recommendations. When analyst i initiates coverage for stock j at time t_{ij0}, his initial recommendation of $R_{ij,t_{ij0}}$ is determined by the level of his valuation $V^*_{ijt_{ij0}}$ relative to the recommendation cutoffs $\mu_2 < \mu_3 < \mu_4 < \mu_5$ that he sets. Analyst i initiates coverage with a strong buy if $V^*_{ij,t_{ij0}} \geq \mu_5$, and with an appropriate lower recommendation if $V^*_{ij,t_{ij0}}$ falls into the corresponding valuation bin. Thus,

$$R_{ij,t_{ij0}} = \begin{cases} 5, & \text{if } \mu_5 \leq V^*_{ijt_{ij0}} \\ 4, & \text{if } \mu_4 \leq V^*_{ijt_{ij0}} < \mu_5 \\ 3, & \text{if } \mu_3 \leq V^*_{ijt_{ij0}} < \mu_4 \\ 2, & \text{if } \mu_2 \leq V^*_{ijt_{ij0}} < \mu_3 \\ 1, & \text{if } \qquad V^*_{ijt_{ij0}} < \mu_2. \end{cases} \tag{3}$$

[11]The variance just multiplicatively scales the cutoffs for recommendations and revisions.

A recommendation of a 5 represents a strong buy, 4 is a buy, 3 is a hold, 2 is a sell, and 1 is a strong sell. Without loss of generality, for identification purposes, we normalize μ_2 to zero.[12]

Subsequent recommendations R_{ijt} are determined by both the analyst's updated valuation V^*_{ijt} and his outstanding recommendation $R_{ij,t-1}$. Our model captures an analyst's reluctance to change recommendations via the recommendation-specific revision frictions that the analyst introduces. Specifically, if analyst i's outstanding recommendation for stock j at time t is $R_{ij,t-1} = k$, then analyst i would not lower his recommendation R_{ijt} to $k-1$ unless his valuation V^*_{ijt} falls below the threshold value μ_k by an amount $\delta_{k\downarrow}$ that the analyst chooses. Similarly, analyst i will not raise his recommendation R_{ijt} to $k+1$ unless $V^*_{ijt} > \mu_{k+1} + \delta_{k+1,\uparrow}$. In effect, the analyst expands the bin corresponding to his previous recommendation k from $[\mu_k, \mu_{k+1})$ to $[\mu_k - \delta_{k\downarrow}, \mu_{k+1} + \delta_{k+1,\uparrow})$, and does not revise his recommendation unless his valuation assessment V^*_{ijt} evolves outside of this expanded bin. See Figure 3. Such revision frictions are "localized" in that (a) the extents to which a recommendation bin is expanded can depend on the recommendation itself (i.e., $\delta_{k+1,\uparrow}$ and $\delta_{k\downarrow}$ can vary with k), and (b) revision frictions only affect decisions to upgrade or downgrade to "adjacent" recommendations. For example, if an analyst has an outstanding strong sell ($R = 1$) rating, the friction $\delta_{2\uparrow}$ only affects upgrades to a sell: as long as $\mu_3 > \mu_2 + \delta_{2\uparrow}$, this friction has no effect on upgrades to hold. Therefore, the probability distribution over analyst i's recommendations for stock j at time t is

$$\Pr\left[R_{ijt} = k | X_{ijt}, R_{ij,t-1}\right] = \begin{cases} \Pr\left[\mu_k \leq V^*_{ijt} < \mu_{k+1}\right], & \text{if } R_{ij,t-1} > k+1, \\ \Pr\left[\mu_k \leq V^*_{ijt} < \mu_{k+1} - \delta_{k+1,\downarrow}\right], & \text{if } R_{ij,t-1} = k+1, \\ \Pr\left[\mu_k - \delta_{k\downarrow} \leq V^*_{ijt} < \mu_{k+1} + \delta_{k+1,\uparrow}\right], & \text{if } R_{ij,t-1} = k, \\ \Pr\left[\mu_k + \delta_{k\uparrow} \leq V^*_{ijt} < \mu_{k+1}\right], & \text{if } R_{ij,t-1} = k-1, \\ \Pr\left[\mu_k \leq V^*_{ijt} < \mu_{k+1}\right], & \text{if } R_{ij,t-1} < k-1, \end{cases} \tag{4}$$

where we adopt the convention that $\mu_1 = -\infty$ and $\mu_6 = +\infty$. This formulation allows for distinct recommendation-specific frictions for both upgrades and downgrades, i.e., $\delta_{k\uparrow} \neq \delta_{k\downarrow}$. The model nests the ordinary probit model and $\delta_{k\uparrow} = \delta_{k'\downarrow} = 0, \forall\ k, k'$, captures the "idealized" financial analyst.

Analysts are reluctant to adjust recommendations too often for several reasons, and revision frictions are a tractable, parsimonious way to capture this strategic reluctance. First, repeatedly revised recommendations make it harder for investors to draw inferences about an analyst's ability. Since less frequent changes make it easier to draw inferences about ability,

[12]In the estimation of an ordered probit model, it is standard practice to set the lowest cutoff (μ_2) to 0 because recommendations reflect *differences* between cutoffs and valuation, precluding joint identification of the cutoff and the constant term β_0 of an analyst's valuation model.

able analysts tend to revise infrequently, forcing less able ones to mimic, else they reveal themselves.[13] Trueman (1990) shows that analysts may be reluctant to revise forecasts upon the receipt of new information due to the negative signals such revisions provide concerning the accuracy of their prior information. In effect, such reputation concerns induce analysts to introduce recommendation revision frictions.

Second, retail investors who base trading decisions on recommendations would be upset were recommendations repeatedly revised. One can only imagine the fury of retail customers who purchased on the basis of a fresh Buy that was revised down to a Hold one day later, causing them to sell, only to be revised back to a Buy three days later.

In our framework, these two forces translate into an analyst only revising a recommendation when an assessment moves far enough away from its associated recommendation bin—there is an opportunity cost to revising a recommendation from a hold to a 'near buy' when a subsequent fall in assessment may be likely, in which case the analyst would want to revise back to a hold. In effect, these forces induce analysts to introduce recommendation revision frictions.

Third, revision frictions also capture analysts' limited attention, which Hirshleifer and Teoh (2003) argue is a consequence of the vast amount of available information and analysts' limited information processing capacities.[14] Gathering and analyzing information to determine whether a revision is warranted is costly. Having intensively analyzed one stock, an analyst mostly will turn to another, as the cost of reanalysis is high relative to the benefit; an analyst will defer to an outstanding rating in between, barring major changes in public or private valuation components.[15] Revision frictions are a computationally tractable way to capture whatever temporal frictions remain with monthly observations.

By construction, the stickiness parameters measure "reluctance to change". They only affect recommendations once an analyst has initiated coverage, which leads to different decision rules for new recommendations vs. revisions (equations 3 vs 4). Reflecting an analyst's

[13] Chen, Francis, and Jiang (2005) argue that analysts can signal their ability by adopting a threshold strategy where they issue forecasts only when their private signals exceed a threshold level; see also (Ottaviani and Sørensen, 2006).

[14] Choi and Gupta-Mukherjee (2015) show that the limited attention of security analysts, as reflected in their propensity to rely on category-level as opposed to firm-level information, has a significant relation with their forecast accuracy. Dong and Heo (2014) show that analysts' forecast behavior is affected by the limited attention or effort allocated to their work during influenza epidemics.

[15] This explanation is consistent with the observation that revisions often piggyback on earnings announcements and major corporate news releases (Ivković and Jegadeesh, 2004,; Altınkılıç and Hansen, 2009), which draw analysts' attention back to the firm.

reluctance to revise, the two cutoffs defining the outstanding recommendation bin are shifted further away (by $\delta_{k\uparrow}$ and $\delta_{k\downarrow}$, respectively), from the cutoffs for new recommendations.

To summarize, Equations (1) – (4) lay out the model's econometric structure. Equations (1) and (2) capture the dynamics of analyst stock valuations, while equations (3) and (4) govern analyst decisions on initial recommendations, and subsequent revisions and reiterations.

2.2 Overview of model estimation and parameter identification

This section outlines the parameter estimation procedure, and the sources of parameter identification. The appendix provides more details on the estimation method and the metrics used to evaluate the goodness of fit of alternative model specifications. It is noteworthy that we are the first to develop and estimate a dynamic latent variable model that allows for temporal adjustment of cutoffs and serial correlation in the error terms. Our analysis also highlights the usefulness of Bayesian MCMC methods in accounting research.

In practice, we observe X_{ijt}, but not V^*_{ijt}. That is, V^*_{ijt} is a latent variable. Under the twin assumptions of conditional independence of R_{ijt} (i.e. $\delta_{k\uparrow} = \delta_{k\downarrow} = 0$) and u_{ijt} (i.e., $\rho = 0$), MLE can be used to estimate the ordered probit model for an idealized analyst. This is because, in this case, the joint likelihood of all observed recommendations becomes the product of individual likelihood functions defined through a standard normal distribution, and the latent variable V^*_{ijt} does not explicitly enter the expression.

However, for a reluctant analyst, the probability distribution of a recommendation (see equation (4)) is highly nonlinear involving the outstanding recommendations and many unknown parameters. The presence of the outstanding recommendation in the probability distribution renders the model path-dependent: to derive the conditional probability of R_{ijt} ($\Pr(R_{ijt}|I_{t-1})$ where I_{t-1} is the information set at time $t-1$), one first needs to do so for $R_{ij,t-1}$, which traces back to $R_{ij,t-2}$, and then to $R_{ij,t-3}$,.... The likelihood function explodes as one tries to model the entire evolution of recommendations issued by all analysts for all firms over the sample period. This makes frequentist approaches (e.g., MLE or GMM) computationally impractical—common optimization algorithms (e.g., Newton–Raphson or BHHH methods) cannot solve the associated maximization problems.[16]

In contrast, Bayesian approaches estimate parameters via repeated sequential updating.

[16]MLE is difficult to implement even for an ordered probit model with serial correlation in the error term and no revision frictions. See Greenberg (2007).

We only need to formulate the *conditional* (posterior) distribution of observing R_{ijt} given the observation of $R_{ij,t-1}$. Then, moving to the next period, the parameter is updated in light of the newly introduced evidence ($R_{ij,t+1}$, $X_{ij,t+1}$, etc.) conditional on the information realized at time t (e.g., R_{ijt}). For instance, conditioning on all other parameters and the value of V^* drawn from its posterior distribution, β and ρ are estimated in a linear regression fashion. In particular, ρ is estimated by regressing u_{ijt} $(= V^*_{ij,t} - X'_{ij,t}\beta)$ on $u_{ij,t-1}$ $(= V^*_{ij,t-1} - X'_{ij,t-1}\beta)$, essentially an OLS estimator of equation (2). Due to its conceptual simplicity and tractability, Bayesian MCMC methods are generally used to estimate discrete choice models that relax conditional independence (see Geweke, Keane and Runkle, 1994, 1997; Keane and Sauer, 2010; or Norets, 2009). Appendix A provides details of our estimation procedure including the conditional distributions for each sets of parameters.

Bayesian MCMC methods do have drawbacks. One must specify prior distributions for the unknown parameters. Inappropriate choices of priors can affect estimates, especially in small samples. We address this by conservatively using uninformative prior distributions that contain minimal prior information about the true parameters.[17] Moreover, due to our large sample, the impact of initial distributional assumptions is tiny. Also, estimation of our complex model is computational demanding and time consuming (albeit computationally feasible, unlike GMM or MLE), as one must repeatedly update the conditional posterior distribution and keep drawing from it many thousands of times to obtain inferences on parameters.[18]

Parameter identification. The major sources of identification for cutoffs μ are initial recommendations and multi-level revisions (e.g., from Sell to Buy). This is because revision frictions do not enter the probability of initial recommendations (see equation (3)) or multi-level revisions. Thus, as with a standard ordered probit approach, the μ_j parameters are estimated by mapping V^* to the initial ratings. As mentioned above, the persistence of private information, ρ is estimated by regressing u_{ijt} $(= V^*_{ij,t} - X'_{ij,t}\beta)$ on $u_{ij,t-1}$ $(= V^*_{ij,t-1} - X'_{ij,t-1}\beta)$.

Identification of revision frictions ($\delta_{k\uparrow}$ and $\delta_{k\downarrow}$) largely comes from situations in which an

[17] For instance, we assume that the prior of ρ is drawn from a truncated normal distribution, $\rho \in (-1, 1)$, with mean 0.5 and a large standard deviation of 1 [i.e., $N(0.5, 1) \times I(|\rho| < 1)$]. As we keep updating the distribution of ρ given the estimates of other parameters, the posterior distribution, which incorporates this uninformative prior belief of ρ, eventually converges to the true sampling distribution. Alternatively specifying the prior of ρ as a uniform distribution on $(-1, 1)$ has no observable impact on parameter estimates.

[18] Computation time for each model is about 7 days. The computational burden is mainly due to the slow convergence of the Monte Carlo Markov chains for cutoff estimates. The slow convergence in the cutoff estimates μ_k is due to the narrow interval of its conditional uniform distribution, which limits how far a cutoff estimate can move toward its true value in one iteration. Similar findings obtain for estimation of the independent multinomial model (Cowles, 1996) and autoregressive ordered probit model (Muller and Czado, 2005).

outstanding rating is maintained even though an estimated V^* has crossed a cutoff for the recommendation. A revision friction is invoked when the valuation crosses a cutoff for the outstanding recommendation and thus would trigger an one-level upgrade or downgrade in its absence. Concretely, as V_t^* rises above μ_4, given an outstanding Hold rating and the observation of a reiteration ($R_{t-1} = R_t = 3$), one can infer that $\delta_{4\uparrow}$ exceeds $V_t^* - \mu_4$ (so that $V_t^* < \mu_4 + \delta_{4\uparrow}$), else an upgrade would have been triggered. Conversely, when an upgrade is issued, $\delta_{4\uparrow}$ must be less than $V_t^* - \mu_4$ (so that $V_t^* > \mu_4 + \delta_{4\uparrow}$) to warrant the revision. Thus, the sampling distribution of $\delta_{4\uparrow}$, including the corresponding point estimate and inference, can be derived from all one-level upgrades from Hold and reiterations of Hold,[19] while the sampling distribution of the opposing friction $\delta_{4\downarrow}$ can be derived from all one-level downgrades from Buy and reiterations of Buy. Of course, and quite crucially, the four sets of parameters are jointly determined and must be simultaneously estimated via sequential updating in a Bayesian manner.

While both persistent private information and revision frictions reduce revision frequency (see Figures 3 and 4), they work in very different ways. A large value of ρ slows down and smoothes variations in the stock valuation over time, regardless of where that valuation is (i.e., regardless of which recommendation bin it is in, and its location within a bin). Unlike ρ, which has a uniform impact on V^*, revision frictions become relevant only when V^* is close to the relevant cutoff for an outstanding recommendation, and friction values vary across different recommendation levels. For example, as V_{t-1}^* approaches a cutoff for a revision from a Hold to a Buy, no matter how large ρ is, the latest (small) realization of information shock, ε_t can easily push V_t^* above the cutoff, causing an upgrade to a Buy in the absence of revision frictions; while in the next period, a small negative shock of ε_{t+1} can send V_{t-1}^* back below the cutoff, triggering an immediate downgrade back to a Hold. The $\delta_{k\uparrow}$ and $\delta_{k\downarrow}$ frictions prevent revisions triggered by small fluctuations in newly acquired information, and their magnitudes directly gauge the degree and nature of an analyst's reluctance to revise, including, for example, whether an analyst applies asymmetric frictions to upgrades from Hold vs. downgrades from Buy.[20]

[19] We show in the appendix that $\delta_{k\uparrow}$ has a uniform posterior distributed on $[\delta_{k\uparrow low}, \delta_{k\uparrow up}]$, where

$$\begin{aligned} \delta_{k\uparrow low} &= \max_{i,j,\text{ and } t\neq t_{ij0}(s)} \left\{ V_{ijt}^* - \mu_k : R_{ijt} = R_{ij,t-1} = k-1 \right\}, \\ \delta_{k\uparrow up} &= \min_{i,j,\text{ and } t\neq t_{ij0}(s)} \left\{ V_{ijt}^* - \mu_k : R_{ijt} = k,\ R_{ij,t-1} = k-1 \right\}. \end{aligned}$$

[20] Notice that $\Pr[R_{ijt} = k | X_{ijt}, R_{ij,t-1}]$ varies throughout its range with ρ, but changing δ only affects $\Pr[R_{ijt} = k | X_{ijt}, R_{ij,t-1}]$ locally around the relevant recommendation. As a result, if $(\delta', \rho') \neq (\delta, \rho)$, then $P_{(\delta,\rho)}\left(\cdot | \{R_{ijt}, X_{ijt}\}_{i.j.t} \right) \neq P_{(\delta',\rho')}\left(\cdot | \{R_{ijt}, X_{ijt}\}_{i.j.t} \right)$, i.e., the stickiness parameters and persistence

3 Data

Our sample of analyst recommendations is from the Institutional Brokers Estimate System (I/B/E/S) U.S. Detail file. Following most studies in the literature, we reverse the I/B/E/S recommendation coding so that more favorable recommendations correspond to larger numbers (i.e., 1=Strong Sell, 2=Sell, 3=Hold, 4=Buy and 5=Strong Buy). Each analyst is identified by I/B/E/S/ with a unique numerical code (analyst masked code). We use this numerical identifier to match an analyst's stock recommendations to his earnings forecasts in the I/B/E/S Detail History file. We exclude recommendations issued by unidentified/anonymous analysts. Stock return and trading volume related data are collected from CRSP. Firms' accounting and balance-sheet information is extracted quarterly from Compustat.

We use monthly data from January 2003 to December 2010 from the post Regulation Fair Disclosure, post Global Analyst Research Settlement period. If an analyst issues multiple recommendations for a firm within a calendar month, we only use the last recommendation. Our choice of monthly frequencies reflects practical considerations. First, analysts rarely change recommendations more than once in a month (only 1.2% of recommendations in our sample are revised more than once in a month) and analysts may introduce slight temporal revision frictions, to avoid repeated revisions over a short period of time. It is not feasible to allow for temporal frictions in estimation; and monthly observations minimize the impact of temporal frictions on estimates. One might also worry about uneven information arrival due to endogenous information acquisition—an analyst who gathers information about a firm today is less likely to do so tomorrow, leading to lumpiness in information arrival at high frequencies. However, an analyst will monitor a firm more than once a month, so endogenous information acquisition will not lead to lumpy information arrival at monthly frequencies. Second, much of our data is observed at lower frequencies (e.g., sales growth or earnings). Third, monthly frequencies facilitate estimation, as the median time to recommendation revision is 190 days.

Brokerage houses that use three-tier rating systems appear in the I/B/E/S database as issuing either Buy, Hold and Sell (4, 3, 2) recommendations only; or as issuing only Strong Buy, Hold and Strong Sell (5, 3, 1) recommendations. We pool these two populations into a single three-tier rating system.[21] We identify the date at which brokerage houses switch to the three-tier system by the date at which they exclusively issue from that subset (they typically switch on the same day). Our sample of five-tier brokerage houses only includes those that

parameter are separately identified.

[21]Estimates if we do not pool are qualitatively identical.

never switch; and we only use observations on three-tier brokerage houses once they switch.

Analysts who maintain a recommendation from one month to the next do not typically reiterate their recommendations. Analysts also sometimes cease following a stock without indicating a stopped coverage on I/B/E/S. To avoid building in spurious persistence in estimates of an analyst's information and larger recommendation revision frictions by including non-varying recommendations from analysts who ceased following a stock, we conservatively assume that an analyst who does not reiterate or revise a recommendation within 12 months has dropped coverage.[22] Thus, in the absence of a revision, reiteration or stopped coverage indication by analyst i for stock j (an analyst-firm pair) in month t, we set the recommendation, R_{ijt}, to be the most recent recommendation/reiteration issued in the past 12 months by the analyst for that firm. For a given analyst-firm pair, an observed recommendation with no preceding outstanding recommendation in the past year is classified as an initiation, and a recommendation revision/reiteration refers to a recommendation for which there was an outstanding recommendation[23] in the previous month. We exclude analyst-firm pairs with fewer than 20 recommendations (including filled-in reiterations) over the entire sample period. This policy largely eliminates only analysts who *never* revise or reiterate a recommendation, dropping analysts who may have quickly lost interest and ceased following a firm. Our final sample of analysts using a three-tier rating system consists of an unbalanced panel data with 241076 recommendations by 1927 analysts (from 188 brokerage houses) for 2805 firms (8224 analyst-firm pairs); and for analysts using a five-tier rating system, we have 89726 recommendations by 740 analysts (from 128 brokerage houses) for 1894 firms (3059 analyst-firm pairs).

Table 1 presents the distributions of recommendation levels and the transition matrix of recommendation revisions and reiterations for brokerage houses using a three-tier rating system; and Table 2 does so for those using a five-tier rating system. Almost half of the recommendations by brokerages that use three ratings are holds, 41% are buys and 10% are sells. Table 2 shows that brokerage houses that use five ratings are more optimistic—about 53% of their recommendations are strong buys or buys, and only 7% are sells or strong sells—likely reflecting that five-tier brokerage houses, which tend to be smaller, without an investment bank side, have different audiences. This means that one cannot collapse five-tier brokerage houses into three-tier ones by grouping strong buys with buys, and strong sells with sells.

[22] We show that our qualitative empirical findings are robust if we use different cutoffs (e.g., 9 or 15 months) to identify analysts who drop coverage.

[23] This outstanding recommendation may be an actual issuance by the analyst or a carryover from a recent issuance within the past twelve months.

Table 1: Distribution of Analyst Recommendations (three-tier ratings)

Panel A. Stock Recommendation Levels				
	Buy, 4	Hold,3	Sell, 2	Total
Initiations	29910	35862	7172	72944
	41.00%	49.16%	9.83%	100%
Full Sample	99159	118626	23291	241076
	41.13%	49.21%	9.66%	100%

Panel B. Transition Matrix of Recommendation Revisions and Reiterations				
To:	Buy, 4	Hold, 3	Sell, 2	Total
From:				
Buy, 4	65859	3314	100	69273
	95.07%	4.78%	0.14%	100%
Hold, 3	3265	78319	1026	82610
	3.95%	94.81%	1.24%	100%
Sell, 2	121	1127	14993	16241
	0.74%	6.94%	92.31%	100%
Total	69245	82760	16119	

For brokerage houses using a three-tier system, transitions out of buy are about as likely as those out of hold, while upward transitions out of sell are about 50% more likely. Brokerage houses using a five-tier system do not hold negative ratings for as long as those using a three-tier system—they are more likely to revise holds or sells upward, and less likely to revise buy/strong buy ratings down—additional indications that they tailor recommendations more optimistically. Of note, brokerage houses using a five-tier system are more likely to revise recommendations to hold than to other revisions, *even* from strong buy and strong sell.

Public information components of value. We consider a wide range of public available firm- and analyst-specific characteristics (22 explanatory variables) that plausibly enter an analyst's assessment of value, most of which have been suggested by prior studies to be related to recommendations. We further control for industry fixed effects captured by one-digit SIC codes. Appendix B details the sources and definitions of these variables.

Table 2: Distribution of Analyst Recommendations (five-tier ratings)

Panel A. Stock Recommendation Levels

	Strong Buy, 5	Buy, 4	Hold,3	Sell, 2	Strong Sell, 1	Total
Initiations	5476	8137	9960	1519	364	25456
	21.51%	31.96%	39.13%	5.97%	1.43%	100%
Full Sample	19371	28816	35228	5068	1243	89726
	21.59%	32.12%	39.26%	5.65%	1.39%	100%

Panel B. Transition Matrix of Recommendation Revisions and Reiterations

To:	Strong Buy, 5	Buy, 4	Hold,3	Sell, 2	Strong Sell, 1	Total
From:						
Strong Buy, 5	12911	395	499	9	2	13816
	93.45%	2.86%	3.61%	0.07%	0.01%	100%
Buy, 4	498	19355	900	58	12	20823
	2.39%	92.95%	4.32%	0.28%	0.06%	100%
Hold,3	474	869	23512	251	60	25166
	1.88%	3.45%	93.43%	1.00%	0.24%	100%
Sell, 2	6	51	299	3220	23	3599
	0.17%	1.42%	8.31%	89.47%	0.64%	100%
Strong Sell, 1	6	9	58	11	782	866
	0.69%	1.04%	6.70%	1.27%	90.30%	100%
Total	13895	20679	25268	3549	879	

4 Empirical Analysis

We next present estimates of our model of analyst recommendations. We compare results from the full model (detailed in equations (1)–(4)) with those from more restricted models to emphasize the importance of both information persistence and revision frictions in the analyst decision-making process. We then investigate the indirect implications of the model for the duration of recommendations and market reactions to recommendations.

Table 4 reports the parameter estimates. Columns 1 to 5 present restricted models for the three-tier rating system and Column 6 presents the full model. Column 7 presents the full model for the five-tier rating system. The bottom two rows show the Brier score and the logarithm of the marginal likelihood of a particular model used to assess the goodness of model fit.

The ordered probit model captures an idealized analyst who employs no recommendation frictions and has no persistent valuation information that the econometrician does not see. This model is nested in our framework when δ and ρ are set to zero. Columns 1 and $1'$ present parameter estimates of an ordered probit model obtained using our MCMC approach and conventional maximum likelihood, respectively. The two methods yield nearly identical parameter estimates. We defer discussion of the publicly-available determinants of stock valuation to the full model.

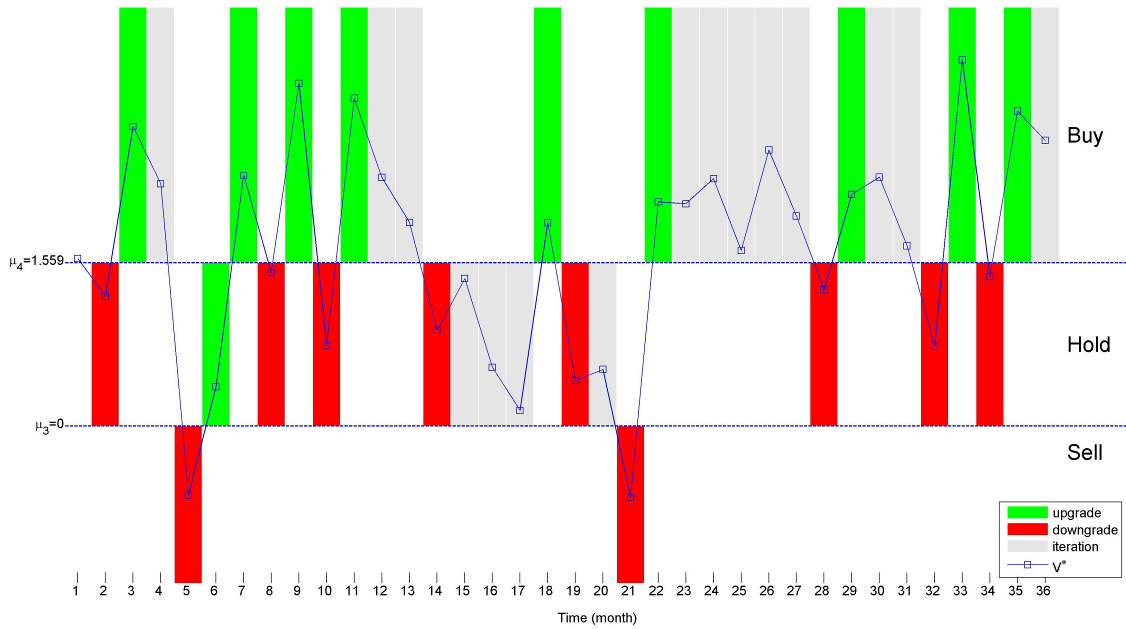
The ordered probit model fits the data *poorly.* The poor fit is reflected in the large Brier score, which reveals a large discrepancy between predicted probabilities of recommendations and actual outcomes. The ordered probit model fit by maximum likelihood has a pseudo-R^2 of only 2.09%. The key to the bad fit is that no matter how the model of valuation is formulated, it predicts far too many recommendation revisions. Figure 1 presents a sample valuation path: the model predicts 20 recommendation revisions over the 36 month period, and there would be far more if we used weekly observations. In essence, while there is some persistence in recommendations due to persistence in public information data and quarterly arrival of earnings information (i.e., there is persistence in firm and analyst fundamentals in X), there is *far* too little to generate the infrequent recommendation revisions found in the data.

Column 2 considers an idealized analyst who does not set recommendation revision frictions, but does gather information that the econometrician does not have, information that has persistent valuation implications. The autoregressive coefficient estimate is *very* high, $\hat{\rho} = 0.90$, and hugely credible/significant. Incorporating this persistent information source cuts the Brier score almost in half, from 0.34 to 0.18, and it is accompanied by an enormous Bayes factor of exp(49740): accounting for the temporal correlation in an analyst's information yields a *vast* improvement in model fit.

The high persistence in analyst information reduces the frequency of recommendation revisions. To see why, consider a stock with a valuation in month $t-1$ of $V^*_{t-1} = 4.2$, which is well above the Buy rating cutoff of 3.5. If an analyst receives a one standard deviation positive information shock ($\varepsilon_t = +1$), raising V^*_t to 5.2,[24] the slow decay means that it is likely to take a long time for the valuation to drop out of the buy bin. Conversely, a one-standard deviation negative shock ($\varepsilon_t = -1$) leads to a downgrade to Hold as V^*_t drops to 3.2. However, the valuation would slowly revert, rising due to the decay of ε_t. Absent arrival of

[24]For the purpose of this illustration, assume that u_{t-1} is 0.

Figure 1: Idealized analyst



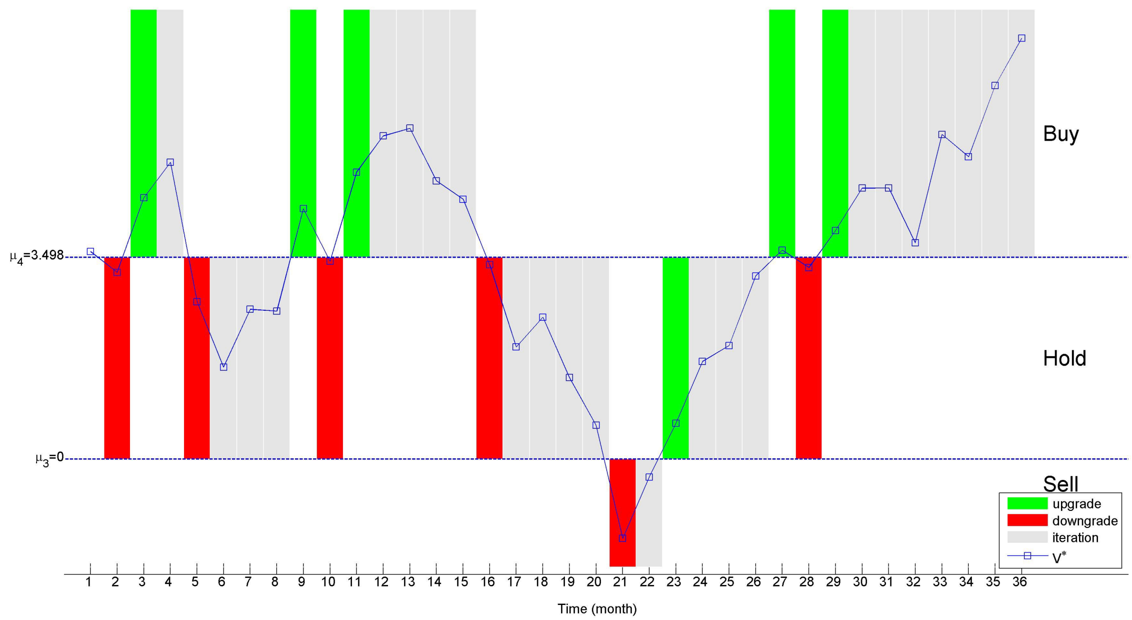
Recommendation cutoffs, and sample valuation and recommendation paths over a 36-month period for an idealized analyst employing a three-tier rating system whose private information is transient.

other information, the analyst would switch back to a buy recommendation after 4 months.

Figure 2 depicts equilibrium bins for an idealized analyst with persistent information, and it illustrates sample valuation paths *for the same common public information valuation path and information shocks as Figure 1.* Persistent information reduces the number of recommendation revisions from 20 to 12. Still, the data remain badly described by an idealized analyst: Regardless of the persistence in analyst information, an idealized analyst *cannot* deliver low likelihoods of recommendation revisions when the valuation is close to a ratings cutoff because small price fluctuations would lead to repeated crossings of the cutoff.

To generate the high stickiness in recommendations implicit in the small off-diagonal transition probabilities in Table 1, one needs recommendation revision frictions strategically introduced by analysts who value intertemporal consistency in recommendations. Columns 3 to 6 present estimates of such models. Column 3 presents estimates for a model with (a) only two friction parameters, $\delta_{\uparrow}$ and $\delta_{\downarrow}$, one for upward revisions and one for downward revisions, when (b) analysts have no persistent information. Both revision friction estimates are *large* and highly significant. Model 3 has a *far* better goodness of fit than model 2 (Bayes factor of $exp(75014)$), indicating that the reluctance of analysts to revise recommendations is an even

Figure 2: Idealized analyst with persistent information



Recommendation cutoffs, and sample valuation and recommendation paths over a 36-month period for an idealized analyst who has persistent information. The sample valuation path uses *the same common public information valuation path and information shocks as Figure 1.*

more important driver of recommendations than persistent information. Importantly, there would be little impact on estimates were higher frequency (e.g., bi-weekly) recommendation observations used, because valuations rarely change sharply over short windows: small changes in valuations *cannot* lead to successive changes in recommendations. In this way, recommendation revision frictions also capture temporal stickiness in recommendations.

Column 4 presents estimates of a model with the same two recommendation frictions, $\delta_\downarrow$ and $\delta_\uparrow$, *and* persistent analyst information, where we now *discard all* publicly-available information except the constant. There is a further improvement in model fit (Bayes factor $exp(6646)$), revealing that the information available to the econometrician matters far less for explaining the dynamics of recommendations than do recommendation revision frictions and persistent analyst information.

Column 5 presents estimates of model 5, which augments model 4 with all public information variables. The Bayes factor for models 3 and 5 of $exp(13324)$ is again very large: persistent analyst information and recommendation revision frictions are complementary sources of improved model fit. These complementarities are also indicated by the huge ratios of the mean to standard deviation of parameter estimates: 85.5 for the information persistence parameter ρ, 266.9 for $\delta_{\uparrow}$ and 403.4 for $\delta_{\downarrow}$. This means that persistent analyst information and recommendation revision frictions capture distinct economic phenomena—*persistent analyst information is not a proxy for an unwillingness of analysts to revise recommendations.* Failing to account for both sources of stickiness biases estimates significantly.

Column 6 presents estimates for our full model, in which analysts have persistent private information and recommendation revision frictions can vary with the recommendation itself and $\delta_{k\uparrow}$ can differ from both $\delta_{k\downarrow}$ and $\delta_{k'\uparrow}$. That is, analysts do not need to use symmetric recommendation revision frictions to reduce the frequency of recommendation revisions; they can tailor them to reflect other considerations (see Figure 3).

The full model fits the recommendation data the best. It has the smallest Brier score of 0.141 and the large Bayes factor of $exp(7134)$ versus model 5 provides conclusive evidence against the other models. Figure 4 depicts the equilibrium bins for the full model, and it illustrates sample valuation paths *for the same common public information valuation path and analyst information shocks as Figures 1 and 2.* The figure hints at why the model fit is so much better: only 4 revised recommendations are issued over the 36 month period. Inspection of the estimates of the cutoff-specific revision frictions provides more insights: their magnitudes vary sharply, indicating that the more restricted models are significantly mis-specified. For example, frictions out of hold are much smaller than those into hold, and a single one-directional friction cannot account for this. The more flexible formulation of the recommendation-specific revision frictions reduces the analyst's information as a source of persistence in recommendations by almost 25%.

Table 3: Parameter Estimation

Model	**(1)**	**(1')**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Recommendation Cutoffs								
μ_5								4.340
								(526.7)
μ_4	1.559	1.565	3.498	1.782	1.745	1.787	1.966	2.910
	(384.3)	(405.6)	(364.4)	(370.0)	(339.3)	(392.9)	(455.9)	(374.1)
μ_3	0	0	0	0	0	0	0	1.154
								(140.33)
μ_2								0
Persistence of Information								
ρ			0.895		0.401	0.389	0.313	0.609
			(607.4)		(85.47)	(83.73)	(66.15)	(116.9)
Recommendation Revision Frictions								
$\delta_{\uparrow}$				1.445	1.337	1.346		
				(974.0)	(266.9)	(262.7)		
$\delta_{\downarrow}$				1.631	1.525	1.553		
				(954.7)	(403.4)	(394.5)		
$\delta_{5\uparrow}$								1.174
								(43.17)
$\delta_{5\downarrow}$								1.324
								(151.6)
$\delta_{4\uparrow}$							1.336	1.037
							(147.5)	(165.3)
$\delta_{4\downarrow}$							1.563	1.209
							(291.3)	(75.29)
$\delta_{3\uparrow}$							1.787	1.509
							(358.2)	(104.0)
$\delta_{3\downarrow}$							0.822	0.814
							(91.11)	(41.52)
$\delta_{2\uparrow}$								1.136
								(117.1)

Continued on next page

Table 3 – continued from previous page

parameter	(1)	(1')	(2)	(3)	(4)	(5)	(6)	(7)
$\delta_{2\downarrow}$								1.207
								(10.29)
Publicly-available Characteristics								
$const$	0.713	0.713	1.092	0.768	1.480	0.690	1.251	2.897
	(18.02)	(15.76)	(12.43)	(14.82)	(375.84)	(11.48)	(12.61)	(12.53)
ret_{-1}	0.001	0.001	−0.000	−0.001		−0.002	−0.004	−0.002
	(4.63)	(4.58)	(−1.72)	(−4.83)		(−6.93)	(−8.58)	(−4.39)
$ret_{-2:-6}$	0.001	0.001	0.001	0.001		0.001	0.001	0.001
	(4.92)	(5.00)	(4.24)	(6.58)		(5.15)	(3.84)	(1.25)
$ret_{-7:-12}$	0.002	0.002	0.002	0.002		0.002	0.002	0.001
	(18.77)	(18.94)	(13.08)	(13.57)		(11.31)	(7.13)	(2.85)
$\sigma_{-1:-6}$	0.002	0.002	0.004	0.003		0.003	0.002	−0.001
	(8.68)	(8.76)	(6.28)	(7.79)		(6.54)	(3.08)	(−0.75)
$\log(turnover_{-1:-6})$	−0.042	−0.040	−0.076	−0.056		−0.049	−0.042	−0.026
	(−9.06)	(−8.99)	(−7.01)	(−8.98)		(−6.89)	(−3.75)	(−2.23)
$\log(MktCap_{-1:-6})$	−0.053	−0.053	−0.175	−0.058		−0.072	−0.025	−0.041
	(−19.44)	(−19.47)	(−28.12)	(−16.20)		(−17.34)	(−3.62)	(−2.48)
$\log(num\_anal)$	0.115	0.115	0.310	0.110		0.134	0.060	0.117
	(22.26)	(22.40)	(23.71)	(15.88)		(16.27)	(4.84)	(4.50)
$HSize$	−0.080	−0.080	−0.167	−0.067		−0.077	−0.051	−0.120
	(−35.34)	(−35.65)	(−31.70)	(−23.11)		(−22.26)	(−9.40)	(−8.81)
SUE	0.035	0.035	0.051	0.011		0.015	0.017	0.034
	(12.78)	(12.83)	(11.54)	(2.69)		(3.35)	(3.27)	(4.02)
$SUE \times D_{EA}$	0.029	0.030	0.018	0.026		0.024	0.025	0.017
	(6.00)	(6.06)	(4.87)	(5.54)		(5.17)	(4.50)	(2.35)
BM	−0.112	−0.110	−0.256	−0.102		−0.113	−0.080	−0.149
	(−12.61)	(−12.49)	(−13.06)	(−8.50)		(−8.18)	(−3.81)	(−3.40)
EP	0.134	0.135	0.033	0.014		0.006	0.035	0.117
	(3.89)	(3.92)	(0.44)	(0.29)		(0.11)	(0.44)	(0.69)
SG	0.323	0.325	0.679	0.274		0.306	0.177	0.322
	(26.40)	(26.58)	(24.85)	(17.09)		(16.28)	(5.88)	(5.29)

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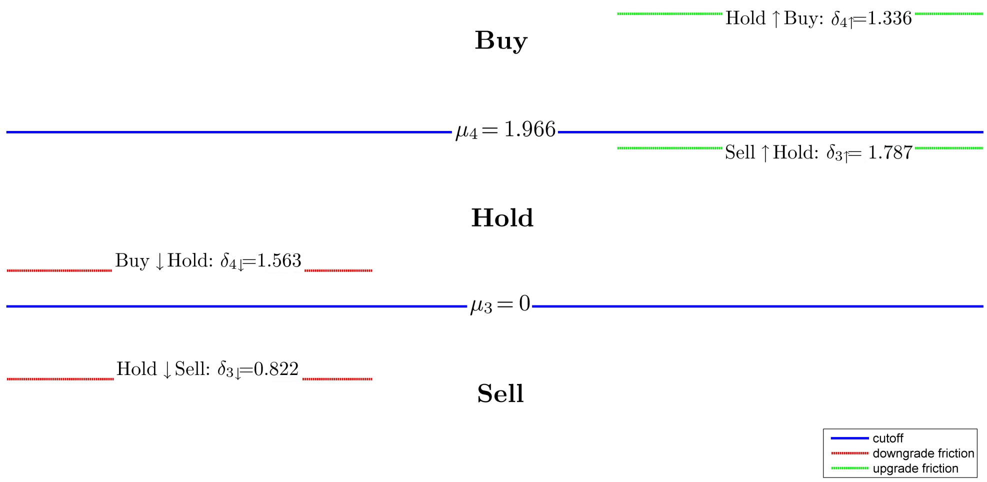
Table 3 – continued from previous page

parameter	(1)	(1')	(2)	(3)	(4)	(5)	(6)	(7)
ROA	−0.169	−0.167	−0.245	−0.081		−0.116	−0.074	−0.415
	(−5.41)	(−5.39)	(−3.46)	(−1.95)		(−2.43)	(−0.97)	(−2.59)
$FAge$	−0.001	−0.001	−0.003	−0.001		−0.001	−0.001	−0.003
	(−6.04)	(−6.08)	(−9.68)	(−4.99)		(−5.45)	(−0.95)	(−2.57)
$FRtoP$	1.299	1.312	2.330	1.269		1.442	1.434	1.705
	(5.79)	(5.86)	(6.00)	(4.15)		(4.29)	(3.88)	(2.01)
$CFtoP$	2.352	2.347	3.901	2.400		2.469	2.342	2.260
	(10.77)	(10.74)	(9.31)	(8.07)		(7.32)	(4.65)	(2.40)
$FDisp$	−8.411	−8.529	−18.145	−10.867		−10.619	−5.430	−6.975
	(−8.11)	(−8.24)	(−10.07)	(−7.64)		(−6.78)	(−2.42)	(−3.86)
$FDev$	5.493	5.480	13.093	7.188		8.526	8.684	13.091
	(11.44)	(11.38)	(15.52)	(11.04)		(11.72)	(8.13)	(7.46)
IH	0.257	0.256	0.388	0.231		0.221	0.217	0.271
	(21.32)	(21.31)	(13.53)	(14.27)		(11.73)	(7.48)	(4.16)
D_{IB}	0.087	0.087	0.180	0.088		0.095	0.088	0.118
	(6.73)	(6.75)	(6.40)	(5.64)		(5.45)	(4.92)	(6.28)
$\log(year\_brkg)$	−0.066	−0.065	−0.106	−0.056		−0.057	−0.057	−0.054
	(−15.03)	(−14.98)	(−10.57)	(−9.71)		(−8.63)	(−5.11)	(−3.19)
$\log(year\_IBES)$	0.028	0.027	0.047	0.033		0.032	0.043	−0.026
	(5.57)	(5.50)	(3.94)	(4.96)		(4.15)	(3.48)	(−0.99)
Goodness of Fit								
$\#obs$	241076	241076	241076	241076	241076	241076	241076	89726
$\#pair$	8224	8224	8224	8224	8224	8224	8224	3059
$Brier\ score$	0.338		0.180	0.151	0.147	0.144	0.141	0.197
LML	−182194		−132454	−107180	−100534	−93586	−86452	−43881
$pseudo-R^2$		2.09%						

The ratio of the posterior mean to standard deviation is reported in parentheses. The row labeled "LML" shows the logarithm of a model's marginal likelihood, $\log(\Pr(D|M))$.

Figure 3: Cutoff and recommendation revision friction estimates

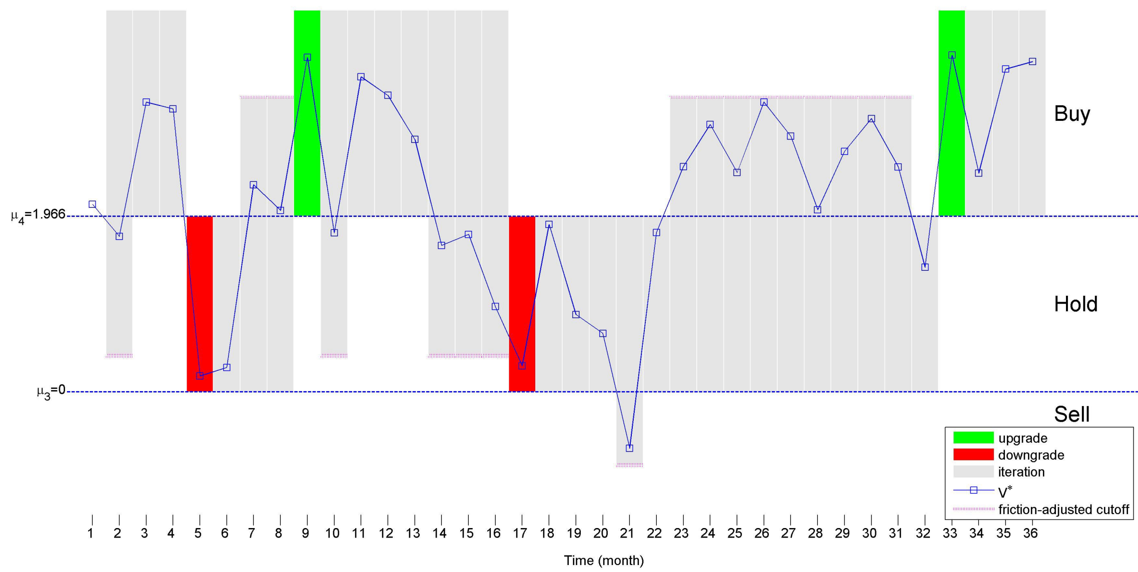


Cutoff and recommendation revision friction estimates of the full model, in which revision frictions are cutoff-specific, and analysts have persistent information. Cutoff-specific revision frictions, $\delta_{k,\downarrow}$ and $\delta_{k\uparrow}$, bear the same index k as cutoff μ_k: $\delta_{k,\downarrow}$ is the friction for downgrades *from* k to $k-1$, while $\delta_{k\uparrow}$ is the friction for upgrades from $k-1$ *to* k.

Column 7 presents estimates for brokerages using five-tier rating systems. Most estimates are qualitatively similar to those for the three-tier system. For example, the recommendation revision friction from sell to hold is far higher than that from hold to sell. Also, the frictions from strong sell to sell and strong buy to buy are *large* relative to the sizes of the sell and buy bins (98% and 92% respectively). As a result, most revisions from strong buy and strong sell are to hold. Thus, the nature of the recommendation revision frictions that five-tier brokerages introduce qualitatively lead them in the direction of behaving like three-tier brokerages.

Still five-tier brokerages *do not* behave like three-tier brokerages: one cannot pool strong buys with buys, strong sells with sells to estimate a homogeneous brokerage using a three-tier rating system. The estimates show that brokerage houses using a five-tier rating system tend to have more optimistic assessments: the average new recommendation initiation for those using five ratings is roughly at the buy/hold cutoff (the constant is 2.9), while that for those using only three ratings is at the 62^{nd} percentile of the hold recommendation bin above the sell cutoff (the constant is 1.3). These differences may reflect that five-tier brokerages, which tend to be smaller, with no investment bank side, are oriented more toward retail investors.

Figure 4: Reluctant analyst



Recommendation cutoffs, and sample valuation and recommendation paths over a 36-month period for a reluctant analyst who has persistent information. The sample valuation path uses the *same common public information valuation path and analyst information shocks as Figures 1 and 2.*

Also, the estimate of information persistence is far higher for five-tier brokerage houses.[25]

Our estimates highlight how analysts design recommendation bins and recommendation revision frictions to carefully balance reputation concerns and the desire to generate trading volume:[26]

- The large frictions out of strong buy and strong sell suggest that revisions to hold generate trading activity by inducing investors to unwind positions, but revisions from strong buy to buy that maintain a positive assessment, or from strong sell to sell that maintain a negative assessment do not.

- Revision frictions *out* of hold are small. Analysts design frictions in and out of hold

[25] One might wonder whether this high estimate could indicate that some analysts at five-tier brokerages act as if they were at three-tier brokerages. Such mis-classification would bias upward estimates of information persistence. However, the many transitions from buy to strong buy and strong buy to buy indicate that any misclassification is minimal.

[26] This is consistent with analysts' economic incentive to boost trading activities (e.g., Eames et al., 2002; Firth et al., 2013).

asymmetrically, with smaller frictions out of hold, so that recommendations spend "less time" in hold, perhaps because *maintained* hold ratings (as opposed to *revisions* to hold) discourage retail investors from trading.

- Analysts are least reluctant to downgrade a stock from Hold—$\delta_{3\downarrow}$ is the smallest among all $\delta_{.\downarrow}$ (see Table 3, Columns 6 and 7 for three- and five-tier systems, respectively). This finding is consistent with the survey evidence in Brown et al. (2015): issuing unfavorable (Sell) recommendations may increase an analyst's credibility with investing clients.

Even though hold revision frictions are small, the model delivers the prevalence of hold recommendations (39% for five-tier brokerages, 49% for three-tier brokerages) in three ways:

- The hold recommendation bin for five-tier brokerages is large, about 25% larger than the buy bin, and 50% larger than the sell bin.
- The estimated average firm for five-tier brokerages is roughly at the buy-hold recommendation cutoff, making an initial hold recommendation likely; and the estimated average firm for three-tier brokerages is slightly above the hold bin midpoint.
- Analysts at five-tier brokerages are less likely to face revision frictions from buy or sell into hold due to the high frictions from strong sell to sell and strong buy to buy, which results in most transitions going from strong buy and strong sell straight to hold.[27]

Our findings make economic sense. The fact that public information available to an econometrician poorly describes recommendations makes sense—if recommendations largely reflected readily-available information, they would have modest value, and one would be hard-pressed to justify why analysts should be well-paid. That the average firm for which coverage is initiated is a hold, but closer to a buy than a sell, supports the notion that analysts tend to follow stocks that they deem to have better prospects. This is consistent with their retail clients being less likely to short-sell, so covering firms with poorer prospects generates fewer client orders. Analysts also want clients to profit from trades—a happy client is likely to trade—so analysts want there to be meaning to buy and sell recommendations, and hence are reluctant to issue such recommendations unless profits are somewhat likely to result.

[27] These estimates also give insight into where improvement in model fit occurs versus more restricted models of five-tier brokerages. Strong sells only comprise 1.4% of the sample, so the two frictions, $\delta_{\uparrow}$ and $\delta_{\downarrow}$ do not weigh transitions from strong sells heavily in the estimation. As a result, $\delta_{\uparrow}$ is far larger than $\delta_{2\uparrow}$. In turn, the large size of $\delta_{\uparrow}$ necessitates a large value for μ_2 (so that transitions from strong sell to sell can occur with positive probability); but then the model cannot deliver few initial sell recommendations.

We now turn to publicly-available determinants of value. Of note, in contrast to existing findings, once we control for a reluctant analyst's information and revision frictions, better past firm performances cease to systematically raise the analyst's assessment: the one month lagged return enters negatively, while more distant returns enter slightly positively. Qualitatively, Column 6 reveals that a reluctant analyst has higher assessments of firms:

- for which the analyst has relatively higher estimated forecasts of earnings (vis à vis the consensus), consistent with Womack (1996) or Jegadeesh et al. (2004).
- that have positive earnings surprise, especially in the earnings announcement window in which they are reported, as in Chan, Jegadeesh and Lakonishok (1996), Jegadeesh, Kim, Krische and Lee (2004), or Ivković and Jegadeesh (2004).
- that draw more attention from other analysts, consistent with more analysts following stocks they believe are undervalued, or possibly analysts valuing a stock's "glamor" (e.g., Barth et al., 2001).
- that are smaller, as measured by higher sales growth (see Lakonishok, Shleifer, and Vishny (1994)) or lower book-to-price ratios (see Jegadeesh et al. 2004)).
- with less turnover, consistent with Lee and Swaminathan (2000), who argue that turnover is a contrarian sign, associated with lower returns.
- about which there is less uncertainty, as captured by forecast dispersion in earnings (see Diether et al. (2002), Zhang (2006)), lesser dispersion in recommendations, or more analyst following or higher institutional holdings.
- for which an analyst's brokerage house has investment banking relationships, consistent with Lin and McNichols (1998), Ljungqvist et al. (2007), Malmendier and Shanthikumar, 2007; O'Brien, McNichols and Lin (2005), Jackson (2005), Cowen, Groysberg, and Healy (2006) and Lim (2001).
- if an analyst is at a smaller brokerage house. Analysts at smaller brokerages also issue more optimistic earnings forecasts (Bernhardt et al. (2006)), and follow smaller firms.
- if an analyst is new at his or her brokerage firm. This is consistent with analysts initially issuing optimistic recommendations in order to generate trading activity, while senior analysts issue more conservative recommendations to preserve reputations.

Quite generally, accounting for revision frictions and persistent analyst information *sharply* reduces the statistical significance/credibility of parameter estimates (relative to the ordered probit model of an idealized analyst), typically by factors of two to five, and the magnitudes of parameter estimates tend to be fall, too. Moreover, recommendation bins are large relative to the valuation consequences of variation in public information available to the econometrician, further indicating that this public information is not the primary driver of recommendations.

Robustness checks. Our econometric model of how analysts form recommendations presumes that sources of heterogeneity between analysts or between the firms for which analysts issue recommendations only enter via the valuation model underlying V, and not the recommendation formation model itself.[28] To assess the validity of this premise, we estimate separate models for subsamples of analysts and firms where one suspects that analysts' recommendations might vary—over time, or by brokerage house size, analyst following or analyst experience. These robustness tests reveal *remarkable* consistency in our estimates.[29] Column 1 of Table 4 reproduces estimates from the full sample. Subsequent columns present estimates for the subsamples of (S1) the second half of the sample period (2006-2010); (S2) large brokerages that on average employed at least 52 analysts over the sample period; (S3) heavily-followed stocks that were covered on average by at least 15 analysts over the sample period; and (S4) senior analysts who have been employed by the same brokerage firm for at least five years. The sample criteria were chosen so that each subsample has roughly half of the original observations.

We see true intertemporal consistency—comparing columns (Full) and (S1) reveals almost no variation in estimates—there is **no** evidence that analysts have altered how they issue recommendations over this period. So, too, the subsample of larger brokerage houses (S2), and senior analysts (S4) have similar estimates. Analyst information is slightly more persistent for heavily-followed stocks, but even this difference is less than 25%, and the other structural recommendation parameters differ by far less. In sum, differences in how vari-

[28] An alternative interpretation of our findings is not that, for example, less experienced analysts (or analysts at smaller brokerages) have higher valuations of firms than more experienced ones (or analysts at larger brokerages), but rather that less experienced analysts (or analysts at smaller brokerages) set systematically lower recommendation cutoffs, reducing all cutoffs by a constant, resulting in higher recommendations. The lack of identification between these two interpretations just reflects that recommendations reflect differences between per share valuations and cutoffs. That is, one can alternatively interpret our framework as accommodating limited heterogeneity in analyst recommendation bins, but not their recommendation revision frictions.

[29] The large ratios of the posterior mean to standard deviation for the structural parameters indicate that they are very precisely estimated. To check this precision, in unreported results, we estimate the model for the subsample of stocks with odd CUSIP numbers. All structural parameter estimates differed by less than 0.01.

ous analysts issue recommendations are well captured by heterogeneity in their models of valuation together with a homogeneous model of recommendation formation and revisions.

Delayed Incorporation of Information by Analysts? Raedy et al. (2006) uncover indirect evidence suggesting that it takes time for analysts to process new information, causing them to under-react to it. This leads us to modify our model to estimate the extent to which analysts fully process new information, deriving direct estimates of the amount by which analysts under-react to new information. We estimate a model in which, of the new information ε_{ijt} that analyst i receives about stock j at time t, he only incorporates a fraction ζ. As a result, the valuation consequences of the analyst's persistent information evolve according to

$$u_{ijt} = \rho(u_{ij,t-1} + (1-\zeta)\varepsilon_{ij,t-1}) + \zeta\varepsilon_{ijt}.$$

The last column of Table 5 presents estimation results for the model in which analysts can under-react to new information. Estimates indicate that analysts incorporate the vast bulk of new information immediately, incorporating all but 9 percent when it arrives. This analysis also shows that delayed incorporation of information does not drive our high estimates of persistence in analyst information and recommendation revision frictions. In fact, allowing for delayed incorporation of information *raises* the estimate of information persistence by about one third. Moreover, changes in estimates of revision frictions are small. The estimates indicate that analysts are "close to rational" in their assessments of new information, and that our qualitative findings are reinforced by integrating this source of modest "irrationality".

Lost Interest? Columns (6m), (9m) and (15m) present estimates when we use alternative cutoffs of 6, 9 or 15 months for the time after which we assume that an analyst has ceased following a stock absent a recommendation revision or reiteration. Longer windows include more analysts who have ceased following a stock, and hence spuriously suggest stickiness, while shorter windows exclude more analysts who are following a stock, but have not reiterated, spuriously suggesting too little stickiness. We see that any reasonable cutoff level has only modest effects on estimates of structural parameters—as one would expect, longer windows for continued coverage slightly raise estimates of persistence and revision frictions.

Table 4: Subsample Analysis

Model	(Full)	(S1)	(S2)	(S3)	(S4)	(6m)	(9m)	(15m)	(delay)
Recommendation Cutoffs									
μ_4	1.966	1.957	1.914	1.888	1.918	1.987	1.978	1.958	1.732
	(455.9)	(512.86)	(238.5)	(369.5)	(417.9)	(507.7)	(489.7)	(509.0)	(293.3)
μ_3	0	0	0	0	0	0	0	0	0
Persistence of Information									
ρ	0.313	0.309	0.342	0.388	0.332	0.289	0.300	0.321	0.430
	(66.15)	(47.96)	(48.30)	(51.93)	(43.85)	(48.71)	(59.83)	(75.75)	(89.66)
delayed incorporation of information									
ζ									0.907
									(336.7)
Recommendation Revision Frictions									
$\delta_{4\uparrow}$	1.336	1.342	1.362	1.400	1.320	1.075	1.220	1.395	1.209
	(147.5)	(112.84)	(104.4)	(69.15)	(67.89)	(100.2)	(185.1)	(332.8)	(220.4)
$\delta_{4\downarrow}$	1.563	1.569	1.562	1.509	1.553	1.536	1.561	1.589	1.335
	(291.3)	(263.02)	(165.7)	(126.1)	(138.1)	(272.3)	(263.5)	(239.9)	(256.1)
$\delta_{3\uparrow}$	1.787	1.756	1.757	1.695	1.746	1.747	1.775	1.820	1.535
	(358.2)	(238.41)	(180.9)	(166.3)	(174.1)	(194.4)	(324.3)	(327.6)	(375.3)
$\delta_{3\downarrow}$	0.822	0.836	0.965	0.921	0.889	0.691	0.786	0.848	0.851
	(91.11)	(48.52)	(51.60)	(30.33)	(36.65)	(51.56)	(89.69)	(83.81)	(221.6)
Publicly-available Characteristics									
ret_{-1}	−0.004	−0.003	−0.004	−0.002	−0.002	−0.004	−0.004	−0.004	−0.004
	(−8.58)	(−5.25)	(−6.28)	(−3.66)	(−3.12)	(−8.43)	(−9.18)	(−9.15)	(−9.75)
$ret_{-2:-6}$	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(3.84)	(3.77)	(2.61)	(2.08)	(2.76)	(4.03)	(4.32)	(3.35)	(2.72)
$ret_{-7:-12}$	0.002	0.002	0.001	0.002	0.002	0.001	0.001	0.001	0.001
	(7.13)	(6.27)	(4.20)	(3.91)	(4.78)	(5.16)	(6.33)	(6.56)	(6.57)
$\sigma_{-1:-6}$	0.002	0.001	0.002	0.002	0.003	0.000	0.001	0.002	0.002
	(3.08)	(0.80)	(1.54)	(1.76)	(2.37)	(0.02)	(1.71)	(2.66)	(2.68)
$\log(turnover_{-1:-6})$	−0.042	−0.053	−0.013	−0.007	−0.064	−0.034	−0.037	−0.039	−0.035
	(−3.75)	(−3.41)	(−0.77)	(−0.29)	(−3.51)	(−2.31)	(−3.02)	(−3.71)	(−2.95)

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Table 4 – continued from previous page

parameter	(6)	(S1)	(S2)	(S3)	(S4)	(6m)	(9m)	(15m)	(delay)
$\log(MktCap_{-1:-6})$	−0.025	−0.007	−0.081	−0.080	−0.025	−0.010	−0.019	−0.029	−0.026
	(−3.62)	(−0.83)	(−7.83)	(−6.59)	(−2.32)	(−1.19)	(−2.60)	(−4.47)	(−3.47)
$\log(num\_anal)$	0.060	0.043	0.099	0.057	−0.020	0.040	0.054	0.057	0.059
	(4.84)	(2.56)	(5.14)	(1.60)	(−1.01)	(2.47)	(4.01)	(4.82)	(4.47)
$HSize$	−0.051	−0.033	−0.370	−0.045	−0.036	−0.015	−0.036	−0.061	−0.051
	(−9.40)	(−4.71)	(−14.04)	(−4.48)	(−4.16)	(−2.37)	(−6.46)	(−11.59)	(−8.61)
SUE	0.017	0.005	0.014	0.014	0.019	0.017	0.015	0.015	0.018
	(3.27)	(0.70)	(2.83)	(2.42)	(2.27)	(2.76)	(2.85)	(3.08)	(3.69)
$SUE \times D_{EA}$	0.025	0.029	0.010	0.020	0.016	0.018	0.027	0.022	0.024
	(4.50)	(3.72)	(2.23)	(2.22)	(1.74)	(2.46)	(4.38)	(4.01)	(4.69)
BM	−0.080	−0.090	−0.102	0.008	−0.145	−0.044	−0.062	−0.071	−0.083
	(−3.81)	(−3.50)	(−3.15)	(0.19)	(−4.14)	(−1.60)	(−2.70)	(−4.13)	(−3.70)
EP	0.035	0.052	0.012	0.071	0.297	−0.057	0.019	0.013	0.034
	(0.44)	(0.55)	(0.09)	(0.45)	(2.10)	(−0.52)	(0.21)	(0.16)	(0.41)
SG	0.177	0.218	0.173	0.169	0.209	0.186	0.158	0.209	0.173
	(5.88)	(5.30)	(3.79)	(3.09)	(4.13)	(4.83)	(5.02)	(7.45)	(5.42)
ROA	−0.074	−0.199	−0.105	−0.061	0.150	0.038	−0.092	−0.032	−0.089
	(−0.97)	(−1.95)	(−0.87)	(−0.43)	(1.10)	(0.38)	(−1.11)	(−0.44)	(−1.11)
$FAge$	−0.001	−0.000	−0.001	−0.001	−0.001	0.000	−0.001	−0.001	−0.001
	(−0.95)	(−0.84)	(−1.28)	(−1.29)	(−0.21)	(0.60)	(−1.21)	(−2.49)	(−0.92)
$FRtoP$	1.434	1.638	0.871	−0.473	1.435	1.453	0.905	0.452	0.372
	(3.88)	(3.09)	(1.18)	(−0.51)	(3.54)	(2.26)	(1.71)	(0.97)	(0.77)
$CFtoP$	2.342	2.041	3.837	1.710	4.365	0.800	1.776	2.264	2.294
	(4.65)	(3.45)	(5.02)	(1.81)	(5.13)	(1.16)	(3.24)	(4.88)	(4.56)
$FDisp$	−5.430	−5.641	−0.646	−15.832	−5.894	−4.856	−7.083	−2.732	−4.554
	(−2.42)	(−2.13)	(−0.19)	(−3.56)	(−1.56)	(−1.65)	(−2.86)	(−1.30)	(−2.09)
$FDev$	8.684	7.557	7.422	8.198	9.134	6.909	7.163	8.911	9.240
	(8.13)	(5.87)	(4.68)	(4.12)	(5.28)	(4.94)	(6.18)	(8.89)	(8.62)
IH	0.217	0.228	0.284	0.151	0.157	0.145	0.194	0.227	0.203
	(7.48)	(5.95)	(6.40)	(2.68)	(3.33)	(3.79)	(6.19)	(8.30)	(6.67)
D_{IB}	0.088	0.083	0.033	0.110	0.046	0.045	0.064	0.077	0.092

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Table 4 – continued from previous page

parameter	(6)	(S1)	(S2)	(S3)	(S4)	(6m)	(9m)	(15m)	(delay)
	(4.92)	(3.15)	(2.50)	(1.35)	(2.81)	(1.00)	(1.46)	(1.66)	(1.86)
$\log(year\_brkg)$	−0.057	−0.060	−0.030	−0.040	−0.014	−0.065	−0.055	−0.050	−0.056
	(−5.11)	(−4.22)	(−1.64)	(−2.12)	(−0.50)	(−4.87)	(−4.21)	(−4.79)	(−4.73)
$\log(year\_IBES)$	0.043	0.062	−0.004	0.067	0.085	0.054	0.039	0.018	0.045
	(3.48)	(3.79)	(−0.19)	(3.01)	(2.72)	(3.41)	(3.07)	(1.59)	(3.41)
const	1.251	1.388	1.422	1.345	1.119	1.256	1.301	1.259	1.098
	(12.61)	(10.48)	(10.91)	(3.75)	(4.80)	(10.07)	(12.24)	(13.52)	(10.24)
Goodness of Fit									
#obs	241076	131067	122133	115739	96522	111455	183870	296164	241076
#pair	8224	6541	4426	4049	3119	4002	6346	9914	8224
Brier score	0.180	0.176	0.188	0.201	0.188	0.186	0.180	0.180	0.136
LML	−86452.0	−54345.6	−51174.1	−54328.3	−40946.2	−48341.3	−77329.5	−127554.1	−75618.0

The ratio of the posterior mean to standard deviation is reported in parentheses. The row labeled "*LML*" shows the logarithm of a model's marginal likelihood, $\log(\Pr(D|M))$.

Indirect Evidence. The goodness of fit measures provide conclusive evidence that our model of a reluctant analyst does a vastly superior job of explaining the dynamics of analyst recommendations than do conventional discrete choice models. We now derive indirect implications of our model, and document additional confirming empirical evidence.

We first show how the reluctant analyst model provides a theoretical framework that can reconcile the differential impacts of recommendation revisions made around significant public information events, such as quarterly earnings announcements. As the most important source of firm-specific information, earnings announcements convey material and "lumpy" information content about earnings, and other key firm characteristics (e.g., sales, margins and investment (Brandt et al. 2008)) that discontinuously shift analyst assessments of firm value. The earnings guidance that firms provide is another channel for lumpy information release. In contrast, information arrival about firm value at other times tends to be smooth.

As a result, recommendation revisions made outside EA or EG windows typically occur when valuation assessments smoothly cross friction-adjusted recommendation cutoffs. In contrast, revisions issued inside these windows are more likely to reflect "jumps" in valuations due to "lumpy" information release. Therefore, following a recommendation revision inside an EA or EG window, the valuation is likely further from the recommendation cutoff, so it will take longer for an analyst's assessment to retrace toward the cutoff for a revision back to the original recommendation than for revisions issued outside these windows.

Moreover, a recommendation *revision* inside an EA or EG window should, on average, convey more valuation information than a revision made outside of those windows. That is, the CAR (cumulative abnormal return) impact of a recommendation revision should be greater inside a window. Importantly, this effect should *not* exist for *new* recommendations as no information is conveyed by an earnings announcement about the *location* of an analyst's assessment of value relative to cutoffs. Via this difference in differences, we control for CAR impacts of information arrival in earnings announcements or guidance that are not due to recommendation revisions (see Ivković and Jegadeesh (2004) or Kecské et al. (2010)).

We focus on recommendation revisions of one-level, as revisions of multiple levels (e.g., from a buy to a sell) necessarily reflect discontinuities in valuation assessments, so one cannot conclude that valuations tend to be closer to cutoffs for recommendations outside EA and EG windows. For revisions of multiple levels, we only predict that they are more likely within these windows than outside, which we find in the data. The EA window is defined as the three-day period on and after the date of a firm's quarterly earnings announcement, where announcements made after close or on a non-trading day are treated as if they occurred on the next trading day. We obtain earnings guidance dates from the First Call Guidelines database and define three-day earnings guidance windows in the analogous way.

Table 5: Retracement durations of revisions inside vs. outside EA windows

Panel A. Retracement durations of one-level revisions				
EA Window	Obs.	Mean	Std. Dev.	95% Conf. Interval
In	6154	158.268	96.924	(155.845, 160.689)
Out	19402	152.064	98.064	(150.683, 153.443)
diff.		6.204***		
		(4.34)		

Panel B. Retracement durations of one-level upgrades				
EA Window	Obs.	Mean	Std. Dev.	95% Conf. Interval
In	3021	163.396	96.563	(159.951, 166.841)
Out	9296	159.705	98.659	(157.699, 161.711)
diff.		3.691**		
		(1.80)		

Panel C. Retracement durations of one-level downgrades				
EA Window	Obs.	Mean	Std. Dev.	95% Conf. Interval
In	3133	153.322	97.028	(149.924, 156.721)
Out	10106	145.034	96.987	(143.143, 146.926)
diff.		8.288***		
		(4.18)		

The row "diff." refers to the difference in average retracement durations of revisions made inside vs. outside EA windows. t-statistics of tests on the equality of means are reported in parentheses. *** and ** denote statistical significance at the 1% and 5% levels.

Panel A in Tables 5 and 6 reports summary statistics of durations (in days) for recommendation revisions to retrace to their original levels. Consistent with predictions, on average it takes 6 days longer for revisions issued inside EA windows to return to their original levels than for revisions made outside *both* windows; and it takes 8 days longer for revisions issued inside EG windows to return. These differences are roughly 5% of the average duration of a revision before retracement. Panels B and C[30] show that it takes 12 days longer for downgrades issued inside EG windows to return than for downgrades issued at other times, whereas the difference is only 2 days for upgrades.[31] This may reflect that negative earnings

[30]No systematic differences in retracement durations emerge for three-tier vs. five-tier brokerages.

[31]One can also use retracement durations as a ball park test for whether analysts set the same cutoffs μ_j for

Table 6: Retracement durations of revisions inside vs. outside EG windows

Panel A. Retracement durations of one-level revisions

EG Window	Obs.	Mean	Std. Dev.	95% Conf. Interval
In	3245	159.859	95.671	(156.566, 163.152)
Out	19402	152.064	98.064	(150.684, 153.443)
diff.		7.795*** (4.21)		

Panel B. Retracement durations of one-level upgrades

EG Window	Obs.	Mean	Std. Dev.	95% Conf. Interval
In	1522	162.179	96.358	(157.335, 167.024)
Out	9296	159.705	98.659	(157.699, 161.711)
diff.		2.474 (0.91)		

Panel C. Retracement durations of one-level downgrades

EG Window	Obs.	Mean	Std. Dev.	95% Conf. Interval
In	1723	157.809	95.040	(153.318, 162.300)
Out	10106	145.034	96.987	(143.143, 146.926)
diff.		12.775*** (5.07)		

The row "diff." refers to the difference in average retracement durations of revisions made inside vs. outside earnings guidance (EG) windows. t-statistics of tests on the equality of means are reported in parentheses. *** denotes statistical significance at the 1% level.

guidance tends to be larger in magnitude than positive guidance, which may take the form of a firm confirming that earnings should be in line with past guidance.

We next explore the implications for market responses to recommendation revisions inside vs. outside earnings announcement and guidance windows. The market reaction is measured by the three-day CAR following a revision issued by analyst i for stock j at day d,

$$CAR_{ijd} = \prod_{d=0}^{2} R_{jd} - \prod_{d=0}^{2} R_M, \tag{5}$$

where R_{jd} and R_M are the raw stock and market daily return, respectively. Day 0 ($d = 0$) is the I/B/E/S reported recommendation date or the following trading day if the recommendation date is not a trading date. We exclude recommendation revisions made on the same day as an announcement or guidance (or the next day if the EA or EG is after close) to

new and revised recommendations. Retracement durations are only slightly longer for new recommendations.

avoid having the CAR reflect both the announcement and the revision.

Table 7: Market reaction to revisions made inside vs. outside EA windows

Panel A. Market reaction to one-level upgrades				
EA Window	Obs.	Mean	Std. Dev.	95% Conf. Interval
In	8221	2.917	7.417	$(2.756, 3.077)$
Out	24488	2.345	7.915	$(2.245, 2.443)$
diff.		0.573^{***} (5.95)		

Panel B. Market reaction to one-level downgrades				
EA Window	Obs.	Mean	Std. Dev.	95% Conf. Interval
In	8518	-3.347	8.841	$(-3.534, -3.158)$
Out	24793	-1.821	8.517	$(-1.926, -1.714)$
diff.		-1.526^{***} (13.87)		

Three-day cumulative abnormal returns (CAR) associated with recommendation revisions issued inside and outside earnings announcement (EA) windows. The row "diff." refers to the difference in average CAR of revisions made inside vs. outside EA windows. t-statistics of tests on the equality of means are reported in parentheses. *** denotes statistical significance at 1% level.

Table 8: Market reaction to revisions made inside vs. outside EG windows

Panel A. Market reaction to one-level upgrades				
EG Window	Obs.	Mean	Std. Dev.	95% Conf. Interval
In	4163	3.401	7.629	$(3.169, 3.633)$
Out	24488	2.345	7.915	$(2.245, 2.443)$
diff.		1.056^{***} (7.66)		

Panel B. Market reaction to one-level downgrades				
EG Window	Obs.	Mean	Std. Dev.	95% Conf. Interval
In	4756	-4.802	9.009	$(-5.057, -4.546)$
Out	24793	-1.821	8.517	$(-1.926, -1.714)$
diff.		-2.980^{***} (20.71)		

Three-day cumulative abnormal returns (CAR) associated with recommendation revisions issued inside and outside earnings guidance (EG) windows. The row "diff." refers to the difference in average CAR of revisions made inside vs. outside EG windows. t-statistics of tests on the equality of means are reported in parentheses. *** denotes statistical significance at 1% level.

Tables 7 and 8 reveal that consistent with predictions, upgrades issued inside EA and EG windows have far larger market impacts than those issued outside both windows, and these CAR differences are highly significant. We also see that for downgrades, differences in CARs inside vs. outside announcement and guidance windows are much larger—bad announcements or guidance conveys "more" news than good announcements or guidance.

To address the possibility that this approach fails to isolate the effect of a recommendation revision from that of the announcement or guidance, we exploit the fact that discontinuities in valuation assessment in EA and EG windows *only occur for revisions and not for new recommendations*. That is, a *new* recommendation made within an EA or EG window conveys no information about value relative to cutoffs that is distinct from a new recommendation made outside the window. Thus, differences in CARs for new recommendations inside vs. outside these windows control for the direct information arrival associated with earnings announcements or guidance. Tables 9 and 10 present the "difference-in-difference" analysis for revisions vs. new recommendations made inside and outside EA and EG windows, providing further confirmatory evidence. In particular, save for downgrades to sell, all difference-in-differences in CARs are highly statistically significant with the "correct" signs, and their large magnitudes range from over 0.4 percentage points to more than two percentage points.

Table 9: Difference-in-Difference Analysis of CARS for Earnings Announcements

Upgrade to Buy/Strong Buy	In EA Win	Out EA & EG Win	diff	Upgrade to Hold	In EA Win	Out EA & EG Win	diff
Up	3.051***	2.385***	0.666***	Up	2.182***	1.662***	0.520***
	(7.82)	(25.79)	(4.77)		(11.93)	(25.50)	(8.74)
Init	1.487***	1.247***	0.240**	Init	−1.768***	−0.577***	−1.190***
	(4.00)	(37.08)	(2.57)		(14.80)	(15.76)	(13.03)
diff	1.564***	1.137***	0.426***	diff	3.950***	2.240***	1.710***
	(4.70)	(19.86)	(3.22)		(12.24)	(23.99)	(8.77)
Downgrade to Hold				**Downgrade to Sell/Strong Sell**			
Down	−3.267***	−1.568***	−1.699***	Down	−3.755***	−2.430***	−1.325**
	(8.29)	(18.71)	(5.95)		(4.34)	(8.31)	(1.83)
Init	−1.768***	−0.577***	−1.190***	Init	−2.912***	−1.737***	−1.175***
	(13.77)	(14.62)	(12.09)		(6.66)	(17.18)	(4.54)
diff	−1.499***	−0.991***	−0.509***	diff	−0.843***	−0.693***	−0.150
	(4.94)	(14.69)	(3.50)		(3.17)	(4.74)	(0.43)

Difference-in-difference results of CARs for revisions made inside vs. outside earnings announcement windows. The CAR associated with initiations of the corresponding rating is used as the control group. ***, ** and * denote statistical significance at 1%, 5% and 10% levels.

Table 10: Difference-in-Difference Analysis of CARs after Earnings Guidance

Upgrade to Buy/Strong Buy	In EG Win	Out EA & EG Win	diff
Up	3.574***	2.385***	1.189***
	(9.00)	(26.06)	(6.18)
Init	1.730***	1.247***	0.483***
	(5.21)	(37.47)	(3.83)
diff	1.844***	1.138***	0.706***
	(5.35)	(20.08)	(3.99)
Downgrade to Hold			
Down	−4.806***	−1.564***	−3.242***
	(12.56)	(18.77)	(10.26)
Init	−2.718***	−0.579***	−2.139***
	(17.99)	(14.78)	(16.59)
diff	−2.088***	−0.985***	−1.103***
	(7.29)	(14.74)	(5.89)

Upgrade to Hold	In EG Win	Out EA & EG Win	diff
Up	2.230***	1.670***	0.560***
	(11.82)	(25.77)	(9.31)
Init	−2.718***	−0.579***	−2.139***
	(19.32)	(15.91)	(17.86)
diff	4.948***	2.248***	2.700***
	(13.15)	(24.24)	(10.21)
Downgrade to Sell/Strong Sell			
Down	−4.944***	−2.425***	−2.519***
	(3.89)	(8.29)	(2.55)
Init	−4.682***	−1.746***	−2.936***
	(10.03)	(17.56)	(7.97)
diff	−0.262	−0.679***	0.417
	(0.24)	(4.72)	(0.88)

Difference-in-difference results for CARs of revisions made inside vs. outside earnings guidance (EG) windows. The CAR associated with initiations of the corresponding rating is used as the control group. *** and * denote statistical significance at 1% and 10% levels.

Recommendation Surprise and Market Reaction. Loh and Stulz (2011) document that some recommendation revisions are more influential than others. They focus on analyst characteristics and show that some attributes (e.g., experience and reputation) lead to stronger market reactions to revisions. Jegadeesh and Kim (2006) find that stock price responses are stronger following recommendation revisions that are further from the consensus. Bradley et al (2014) show that analysts' recommendations are more likely to surprise the market than either earnings announcements or management guidance.

Our framework provides a distinct explanation for why some recommendation revisions should have different market impacts than others. In particular, our model predicts that some recommendations—those where the public-information assessment of the stock valuation is further from a recommendation cutoff—are more surprising than others, as this indicates the analyst's private information must be greater, in order to lead to a recommendation revision. To see this, consider outstanding Hold recommendations for two combinations of observables with different publicly-perceivable valuations. Then a downward revision to Sell conveys more negative information in the scenario with the higher public valuation assessment of the hold, while an upgrade to Buy conveys more positive information for the scenario with the lower public valuation assessment. Consequently, the market CAR responses should be greater following recommendation revisions in these two scenarios. Indeed, to the extent that the findings of Jegadeesh and Kim (2006) are due to larger private information assessments, i.e., greater surprise, our model provides a theoretical rationale for their findings.

We *conservatively* measure the size of recommendation surprise, $\Delta X\beta$, using the difference between the estimate of valuation based on public information $X\beta$ from the *previous month*, and the recommendation friction-adjusted cutoffs corresponding to the revisions/initiations from our full model:

$$\Delta X\beta \equiv \begin{cases} X\beta - (\mu_k + \delta_{k\uparrow}), & \text{upgrades from } k-1 \text{ to } k; \\ X\beta - (\mu_{k+1} - \delta_{k+1,\downarrow}), & \text{downgrades from } k+1 \text{ to } k; \\ X\beta - \mu_k, & \text{new coverage at } k; \end{cases} \tag{6}$$

where k indexes the recommendation level and we omit analyst, firm and time subscripts for simplicity. For initial coverage, we focus on Buy and Strong Buy recommendations because (a) the sample of analysts initiating coverage with a Sell or Strong Sell is too small; and (b) the information content of an initial Hold recommendation is unclear.

$\Delta X\beta$ reveals information about the private information content in an analyst's stock recommendation initiation or revision. For instance, given a previous Hold recommendation, the stock valuation V^*, which is the sum of the public assessment $X\beta$ and the analyst information component u, must breach the friction-adjusted cutoff $(\mu_3 + \delta_{3\uparrow})$ to be upgraded to Buy. Some of u may be public information—just unobserved by the econometrician—which will add noise to our test, while the rest is private. A large positive $\Delta X\beta$ suggests that an upgrade is widely expected by the market as the public assessment already exceeds the minimum level for triggering such a revision. There should still be a positive market response, reflecting that the market learns that an analyst's private information now exceeds that minimum level. However, the market response should be less than that when $\Delta X\beta$ is very negative, as now an upgrade divulges a positive and potentially large private information component. The market should react more strongly to such a "surprising" revision. A similar argument holds for downgrades and for new coverage that, for example, is initiated at a buy.

We measure market reactions using three-day market-adjusted CARs. To ensure that the observed return is attributable to a recommendation revision, we exclude recommendations issued in a three-day window around (on and after) earnings announcement or guidance dates.[32] Our model predicts that the market should react more strongly to those analysts'

[32] If we do not discard recommendations issued within an earnings announcement window, CAR impacts become slightly stronger for downgrades and initiations, and slightly weaker for upgrades.

judgments that imply material private information. To test this, we first categorize recommendation changes as upgrades, downgrades and initial coverage. Then, within each category, we sort recommendations into four equal-sized groups based on the sizes of their surprises, $\Delta X\beta$. Table 11 reports the average size of recommendation surprise, the average 3-day CAR following the recommendation and its standard deviation for each quartile group for the three-tier system.[33] The vast majority of upgrades have $\Delta X\beta < 0$, and almost all downgrades have $\Delta X\beta > 0$, reflecting that our public information measure is conservatively based on the *previous* month's public information, and, for example, upgrades typically follow improvement in the public information measures in the current month. The quartile groups are ordered from smallest $\Delta X\beta$ (g1) to largest (g4). The row labeled "$g4 - g1$" shows the difference in average CARs between these two groups.

Table 11: Recommendation Surprise vs. Three-day CAR

	Upgrade			Downgrade			Initiation (Buy)		
	Ave $\Delta X\beta$	Ave CAR	Std CAR	Ave $\Delta X\beta$	Ave CAR	Std CAR	Ave $\Delta X\beta$	Ave CAR	Std CAR
$g1$	−1.870	3.751	7.778	1.008	−2.429	8.424	−0.578	2.632	9.606
$g2$	−1.674	3.403	5.542	1.202	−2.861	6.079	−0.398	2.136	4.821
$g3$	−1.478	3.587	6.351	1.379	−2.996	6.929	−0.290	2.175	5.159
$g4$	−0.224	2.638	7.104	2.323	−3.763	7.370	−0.133	2.111	5.681
$g4 - g1$		-1.113^{***}			-1.334^{***}			-0.521^{**}	
		(3.07)			(3.46)			(2.13)	

Equally-weighted quartile portfolios formed by sorting stocks based on the size of recommendation surprise, $\Delta X\beta$. For upgrades and initiations, portfolio $g1$ ($g4$) contains the most (least) surprising ratings. For downgrades, Portfolio $g4$ ($g1$) contains the most (least) surprising ratings. Row $g4$-$g1$ presents the difference in average CAR between portfolios $g4$ and $g1$. t-statistics of tests on the equality of means are reported in parentheses. *** denotes statistical significance at the 1% level.

The least surprising upgrades and initiations are in quartile $g4$, and the least surprising downgrades are in quartile $g1$, where $\Delta X\beta$ is the smallest. The findings in Table 12 reveal that the least surprising recommendations have the smallest market impacts, and the most surprising recommendations have the largest impacts, both strongly consistent with the nuanced predictions of our model. The CAR differences between these portfolio quartiles are always substantial and statistically significant. The CAR difference between the most and least surprising quartiles is 1.1 percentage points for upgrades (more surprising is good news), −1.33 for downgrades (more surprising is bad news), and 0.52 for Buy initiations (more surprising is good news), and each is statistically significant at the 5% level.

[33] Results for the five-tier system are qualitatively similar, albeit less significant.

In sum, our framework sheds light on the market perception of recommendation revisions and coverage initiation. The evidence reveals that the market reacts more strongly to decisions by analysts that are more surprising in the context of our model. This indicates that our model describes how investors believe analysts make recommendations, and that investors value the *private* information revealed by recommendation changes and initiations.

5 Conclusion

We develop a model of how financial analysts formulate recommendations, and show how it captures the rich dynamics in analyst recommendations. Our model incorporates two key features of the recommendation process: (i) analysts acquire information with persistent valuation consequences that the econometrician does not observe, and (ii) analysts revise recommendations reluctantly, introducing frictions to avoid repeatedly revising revisions following small changes in valuation assessments. Our model allows analysts to tailor recommendation revision frictions according to the level of the outstanding recommendation and the direction of a possible revision. Our model nests important existing models as special cases.

Our analysis reveals that analysts behave quite differently from the "idealized" analyst who has been the focus of existing research. We find that analysts introduce large recommendation revision frictions to avoid frequent revisions. Strikingly, publicly-available data on firm and analyst characteristics matters far less for explaining recommendation dynamics than does persistent analyst information and the strategic choice by analysts of recommendation revision frictions. We find that analysts design recommendation frictions asymmetrically—varying with the recommendation and direction of revision. Analysts seem to structure recommendations strategically to generate profitable order flow for their brokerages from their retail clients. For example, analysts introduce smaller frictions "out" of hold recommendations than "into" hold recommendations. We also find that recommendations quickly reflect new analyst information—there is minimal delay in incorporating information.

We also document extensive indirect support for our model in (a) durations of recommendation revisions made inside vs. outside earnings announcement and guidance windows, (b) a difference-in-differences analysis of market (CAR) responses to new vs. revised recommendations and inside vs. outside earnings announcement and guidance windows, and (c) CAR responses as a function of the extent to which an analyst's new recommendation or revision is surprising given the public information available to the econometrician.

Of course, our study has limitations. As the first attempt to model and quantify the sources of stickiness in recommendations and the slow decay of private information, our framework allows for analyst heterogeneity in their valuation models, but **not** in the recommendation revision frictions that analysts set or persistence in private information, and it only allows for limited heterogeneity in the recommendation cutoffs that they set.[34]

Ideally, one would allow for richer heterogeneity in recommendation formation. Indeed, we know that it is important to account for heterogeneity in **forecasts**: more experienced analysts and analysts employed at larger brokerage houses tend to issue more pessimistic forecasts of earnings (Bernhardt et al. 2006, Jegadeesh and Kim 2010). We also find such heterogeneity in recommendations: more experienced analysts and those at larger brokerages tend to issue more pessimistic recommendations. That is, more experienced analysts have lower valuations than less experienced analysts (equivalently, more experienced analysts set systematically higher recommendation cutoffs) and analysts from larger brokerages have lower valuations than those from smaller brokerages, which, in turn, make lower recommendations more likely for analysts with more experience or who come from larger brokerages.

Importantly, our subsample search for such heterogeneity indicates little variation in structural estimates according to brokerage house size, analyst experience or time: more experienced analysts and those employed at larger brokerages do *not* introduce systematically smaller recommendation revision frictions. Moreover, our indirect findings show that the "size" of "recommendation surprise" (given *lagged* public information model components) predicts market responses. This indicates that any mis-specifications due to mis-modeled heterogeneity or un-modeled behavior-distorting incentives (e.g., career concerns, Hong and Kubik (2003); herding, Trueman 1994, Chen and Jiang 2006) on recommendation formation are small enough that we still uncover these relationships. Still, integrating greater heterogeneity into the structural model of recommendations is an important direction for future research.

We also assume away any temporal stickiness in recommendations—controlling for their valuation assessment, analysts are not more reluctant to revise recently-issued recommendations. In essence, we encapsulate any temporal stickiness in recommendations that remains at monthly frequencies into the recommendation revision frictions. Decomposing these two potential sources of stickiness is another important direction to take this research.

[34] Like any ordered probit model, it allows for parallel shifts up or down of recommendation cutoffs because recommendations reflect **differences** between per share valuations and cutoffs. Hence, the same recommendations result if analysts have higher per share valuations or if they, instead, set uniformly lower cutoffs.

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Appendix A: Model estimation

This appendix details the estimation of the model laid out in Equations (1) – (4).

Consider first the simple case where analyst i begins giving recommendations for firm j at time t_{ij0}, and continues until time T. We denote the random sequence of recommendation choices by analyst i for firm j by:

$$\mathbf{R}_{ij} = (R_{ijt_{ij0}}, \cdots\cdots, R_{ijT})'$$

and observations (realizations) of $\mathbf{R}_{ij}$ by

$$\mathbf{r}_{ij} = (r_{ijt_{ij0}}, \cdots\cdots, r_{ijT})',$$

where $r_{ijt} \in [1, 2, 3, 4, 5]$. We denote the vector of unknown parameters by $\theta = (\beta', \mu', \delta', \rho)'$. Then, denoting the information set up to time t by $\mathcal{F}_{t-1}$ (i.e., $\mathcal{F}_{t-1}$ contains information about previous recommendations, updated public information, etc.), given the parameters θ and conditional on the information at the starting date, we have[35]

$$P\left[\mathbf{R}_{ij} = \mathbf{r}_{ij}\right] = P\left[R_{ijt_{ij0}} = r_{ijt_{ij0}}\right] \prod_{t=t_{ij0}+1}^{T} P\left[R_{ijt} = r_{ijt} | \mathcal{F}_{t-1}\right].$$

Given the information at the starting date when coverage is initiated, the probability distribution over initial recommendations is determined by (3), so that

$$P\left[R_{ijt_{ij0}} = r_{ijt_{ij0}}\right] = P\left[\mu_{r_{ijt_{ij0}}} \leq V^*_{ijt_{ij0}} < \mu_{r_{ijt_{ij0}}+1}\right].$$

Because the list of variables used when coverage is initiated differs from later dates (lagged recommendations do not enter when coverage is initiated), we denote the vector of right-hand side variables when coverage is initiated by $\underline{X}_{ij,t_{ij0}}$. The analyst's initial valuation model is

$$V^*_{ij,t_{ij0}} = \underline{X}'_{ij,t_{ij0}} \underline{\beta} + u_{ij,t_{ij0}}.$$

Therefore, from the AR structure of the analyst's information process, equation (2), we have

$$P[R_{ijt_{ij0}} = r_{ijt_{ij0}}] = \Phi\left(\sqrt{1-\rho^2}[\mu_{k_{t_{ij0}}+1} - \underline{X}'_{ij,t_{ij0}}\underline{\beta}]\right) - \Phi\left(\sqrt{1-\rho^2}[\mu_{k_{t_{ij0}}} - \underline{X}'_{ijt_{ij0}}\underline{\beta}]\right). \quad (7)$$

Once coverage has been initiated, the conditional distributions, $P\left[R_{ijt} = r_{ijt} | \mathcal{F}_{t-1}\right]$, are determined by (2) and (4) together. Let the vector of right-hand side variables after coverage has been initiated be X_{ijt}. Then $V^*_{ijt} = X'_{ijt}\beta + u_{ijt}$, and defining

$$g_{ijt}(\theta) = \rho V^*_{ij,t-1} + \left(X'_{ijt} - \rho X'_{ij,t-1}\right)\beta,$$

[35]Throughout, we consider distributions conditional on available information at the date coverage is initiated. To ease presentation, we omit this conditioning in our notation. For example, $\Pr\left[R_{ijt_{ij0}} = r_{ijt_{ij0}}\right]$ denotes the distribution over the initial recommendation conditional on information available then.

we have

$$\begin{aligned}
P\left[R_{ijt} = r_{ijt} | \mathcal{F}_{t-1}\right] \;=\; & 1(r_{ijt} = r_{ij,t-1}) \left[\; \Phi\left(\mu_{r_{ijt}+1} - g_{ijt}(\theta) + \delta_{r_{ijt}+1,\uparrow}\right) \;-\; \Phi\left(\mu_{r_{ijt}} - g_{ijt}(\theta) - \delta_{r_{ijt},\downarrow}\right)\right] \\
& + 1(r_{ijt} = r_{ij,t-1} - 1) \left[\; \Phi\left(\mu_{r_{ijt}+1} - g_{ijt}(\theta) - \delta_{r_{ijt}+1,\downarrow}\right) \;-\; \Phi\left(\mu_{r_{ijt}} - g_{ijt}(\theta)\right)\right] \\
& + 1(r_{ijt} < r_{ij,t-1} - 1) \left[\; \Phi\left(\mu_{r_{ijt}+1} - g_{ijt}(\theta)\right) \;-\; \Phi\left(\mu_{r_{ijt}} - g_{ijt}(\theta)\right)\right] \\
& + 1(r_{ijt} = r_{ij,t-1} + 1) \left[\; \Phi\left(\mu_{r_{ijt}+1} - g_{ijt}(\theta)\right) \;-\; \Phi\left(\mu_{r_{ijt}} - g_{ijt}(\theta) + \delta_{r_{ijt},\uparrow}\right)\right] \\
& + 1(r_{ijt} > r_{ij,t-1} + 1) \left[\; \Phi\left(\mu_{r_{ijt}+1} - g_{ijt}(\theta)\right) \;-\; \Phi\left(\mu_{r_{ijt}} - g_{ijt}(\theta)\right)\right]. \qquad (8)
\end{aligned}$$

Thus, letting $\pi(\theta)$ be the prior, we can write the joint distribution of data and parameters as

$$\pi(\theta, r) = \pi(\theta) \prod_{j=1}^{J} \prod_{i \in I_j} \left\{ P(r_{ijt_{ij0}}) \prod_{t=t_{ij0}+1}^{T} P(r_{ijt} | r_{ij,t-1}) \right\},$$

where r is the vector of all realizations of recommendations, $P(r_{ijt_{ij0}}) = P(R_{ijt_{ij0}} = r_{ijt_{ij0}})$ and $P(r_{ijt}|r_{ij,t-1}) = P\left[R_{ijt} = r_{ijt}|\mathcal{F}_{t-1}\right]$ are defined by (7) and (8).

Analyst recommendations and related firm- and analyst-level control variables represent an unbalanced panel dataset containing observations of many analyst-firm pairs (a particular firm followed by a particular analyst) over multiple time periods, reflecting that an analyst may cease following a stock for some time, but then re-initiate coverage. In this case, analyst i may issue recommendations for firm j in n_{ij} different periods, say $\{t_{ij0}(s), \cdots, t_{ij*}(s),\ s = 1, \cdots, n_{ij}\}$, during $t = 1, ..., T$. If we let

$$H_{ijs}\left(r_{ij}, \theta\right) = \left\{ P(r_{ijt_{ij0(s)}}) \prod_{t=t_{ij0}(s)+1}^{t_{ij*}(s)} P(r_{ijt} | r_{ij,t-1}) \right\},$$

where the probability $P(r_{ijt_{ij0(s)}})$ is defined by (7) and conditional probability $P(r_{ijt}|r_{ij,t-1})$ is given by (8), then the joint distribution of data and parameters is

$$\pi(\theta, r) = \pi(\theta) \prod_{j=1}^{J} \prod_{i \in I_j} \prod_{s=1}^{n_{ij}} H_{ijs}\left(r_{ij}, \theta\right). \qquad (9)$$

In our Bayesian estimation approach, we treat the unobserved (latent) valuations as additional unknown parameters and analyze them jointly with the other parameters (θ) using Markov Chain Monte Carlo (MCMC) methods. Let R denote the observed analyst recommendations, and V denote the latent analyst valuations. We divide the vector of parameters θ into 4 groups: (1) valuation parameters β; (2) recommendation bin parameters

μ_j, $j = 3, 4, 5$; (3) recommendation revision friction parameters δ (i.e., $\delta_{k\uparrow}, \delta_{k\downarrow}$, etc); and (4) the information persistence parameter ρ.

The MCMC estimator using Gibb sampler starts with an initial value $(\theta^{(0)}, V^{(0)})$, and then simulates in turn. Conditional on other parameters and the data, the posterior densities of a subset of parameters can be derived based on the joint density (9) and given priors. For convenience of conditioning, we divide the vector of parameters θ into 4 groups: (1) β; (2) μ_j, $j = 3, 4, 5$; (3) δ; and (4) ρ. This partition brings a relatively simple form to the conditional posterior densities and makes it more tractable to draw random variables from the conditional distributions. In particular, the conditional distributions of each subset of parameters are given below:

1. The conditional distribution of β is normal. We start with the prior $\beta \sim N(0, I)$. To simplify the simulation, we follow the suggestion of Albert and Chib (1993) and condition on the initial observation. Conditional on the data and other parameters, the conditional distribution of β is

$$N(\widehat{\beta}, \widehat{\Sigma}_\beta),$$

where

$$\begin{aligned}
\widehat{\beta} \;&=\; \left[\sum_{j=1}^{J}\sum_{i\in I_j}\prod_{s=1}^{n_{ij}}\prod_{t=t_{ij0}(s)+1}^{t_{ij*}(s)} \left(X_{ijt}-\rho X_{ij,t-1}\right)\left(X'_{ijt}-\rho X'_{ij,t-1}\right)\right]^{-1} \\
&\quad \sum_{j=1}^{J}\sum_{i\in I_j}\prod_{s=1}^{n_{ij}}\prod_{t=t_{ij0}(s)+1}^{t_{ij*}(s)} \left(X_{ijt}-\rho X_{ij,t-1}\right)\left(V^*_{ijt}-\rho V^*_{ij,t-1}\right),
\end{aligned}$$

and variance (inverse precision)

$$\Sigma_{\widehat{\beta}} = \left[\sum_{j=1}^{J}\sum_{i\in I_j}\prod_{s=1}^{n_{ij}}\prod_{t=t_{ij0}(s)+1}^{t_{ij*}(s)} \left(X_{ijt}-\rho X_{ij,t-1}\right)\left(X'_{ijt}-\rho X'_{ij,t-1}\right)\right]^{-1},$$

where $X_{ij0} = 0$.

2. The conditional distribution of ρ is a truncated normal. We start with the prior $N(0.5, 1)I(|\rho| < 1)$. Conditional on the data and other parameters, ρ is normally distributed

with mean $\widehat{\rho}$, and variance $\widehat{\sigma}_\rho^2$, truncated by $|\rho| < 1$, i.e., $\rho \sim N(\widehat{\rho}, \Sigma_\rho) \cdot I(|\rho| < 1)$, where

$$\begin{aligned}\widehat{\rho} &= \left[\sum_{j=1}^{J} \sum_{i \in I_j} \prod_{s=1}^{n_{ij}} \prod_{t=t_{ij0}(s)+1}^{t_{ij*}(s)} \left(V_{ij,t-1}^* - X_{ij,t-1}'\beta\right)^2\right]^{-1} \\ &\quad \sum_{j=1}^{J} \sum_{i \in I_j} \prod_{s=1}^{n_{ij}} \prod_{t=t_{ij0}(s)+1}^{t_{ij*}(s)} \left(V_{ij,t-1}^* - X_{ij,t-1}'\beta\right)\left(V_{ij,t}^* - X_{ij,t}'\beta\right),\end{aligned}$$

and

$$\widehat{\sigma}_\rho^2 = \left[\sum_{j=1}^{J} \sum_{i \in I_j} \prod_{s=1}^{n_{ij}} \prod_{t=t_{ij0}(s)+1}^{t_{ij*}(s)} \left(V_{ij,t-1}^* - X_{ij,t-1}'\beta\right)^2\right]^{-1}.$$

3. The conditional density of $\delta_{k\uparrow}$ is a uniform distribution. Given the data, other parameters ρ, β, μ, and other elements in δ, the conditional density of $\delta_{k\uparrow}$ is proportional to $\pi(\theta, r)$. The bounds of the uniform distribution can be derived based on the following information: (1) at the starting period, the stickiness parameter does not enter, and (2) at other periods, the above likelihood is non-zero when: (i) $\mu_k - \delta_{k\downarrow} \leq V_{ijt}^* < \mu_{k+1} + \delta_{k+1,\uparrow}$ if $R_{ijt} = k$ and $R_{ij,t-1} = k$; (ii) $\mu_k \leq V_{ijt}^* < \mu_{k+1} - \delta_{k+1,\downarrow}$ if $R_{ijt} = k$ and $R_{ij,t-1} = k+1$; and (iii) $\mu_k + \delta_{k\uparrow} \leq V_{ijt}^* < \mu_{k+1}$ if $R_{ijt} = k$ and $R_{ij,t-1} = k-1$, (other cases do not depend on the friction parameters.) Using the above information, we obtain that $\delta_{k\uparrow}$ is uniformly distributed on

$$\left[\delta_{k\uparrow low}, \delta_{k\uparrow up}\right],$$

where

$$\begin{aligned}\delta_{k\uparrow low} &= \max_{i,j,\text{ and } t \neq t_{ij0}(s)} \left\{V_{ijt}^* - \mu_k : R_{ijt} = R_{ij,t-1} = k-1\right\}, \\ \delta_{k\uparrow up} &= \min_{i,j,\text{ and } t \neq t_{ij0}(s)} \left\{V_{ijt}^* - \mu_k : R_{ijt} = k,\ R_{ij,t-1} = k-1\right\}.\end{aligned}$$

Similarly, given the data and other parameters, $\delta_{k\downarrow}$ is uniformly distributed on

$$\left[\delta_{k\downarrow low}, \delta_{k\downarrow up}\right],$$

where

$$\begin{aligned}\delta_{k\downarrow low} &= \max_{i,j,\text{ and } t \neq t_{ij0}(s)} \left\{\mu_k - V_{ijt}^* : R_{ijt} = R_{ij,t-1} = k\right\}, \\ \delta_{k\downarrow up} &= \min_{i,j,\text{ and } t \neq t_{ij0}(s)} \left\{\left(\mu_k - V_{ijt}^*\right) \wedge \left(\mu_k - \mu_{k-1}\right) : R_{ijt} = k-1,\ R_{ij,t-1} = k\right\}.\end{aligned}$$

4. The conditional density of μ_k given the data and other parameters ρ, β, δ, and $\mu_l \neq \mu_k$ is a uniform distribution on the interval $[\mu_{k,low}, \mu_{k,up}]$. The lower bound and upper bound

can be derived in a similar way as those for $\delta_{k\uparrow}$ and $\delta_{k\downarrow}$. In particular, the lower bound is

$$\mu_{k,low} = \max\left\{\mu_{k-1}, \max_s \left[\ V^*_{ijt_{ij0}(s)}\ |R_{ijt_{ij0}(s)} = k-1\right], \mu_{k,l1}, \mu_{k,l2}, \mu_{k,l3}, \mu_{k,l4}\right\},$$

where

$$\begin{aligned}
\mu_{k,l1} &= \max_{t\neq t_{ij0}(s)} \left[\ V^*_{ijt} - \delta_{k+1,\uparrow}|\ R_{ijt} = R_{ij,t-1} = k\right], \\
\mu_{k,l2} &= \max_{t\neq t_{ij0}(s)} \left[\ V^*_{ijt} + \delta_{k+1\downarrow}\ |R_{ijt} = k, R_{ij,t-1} = k+1\right], \\
\mu_{k,l3} &= \max_{t\neq t_{ij0}(s)} \left[\ V^*_{ijt}\ |R_{ijt} = k-1, R_{ij,t-1} > k\right], \\
\mu_{k,l4} &= \max_{t\neq t_{ij0}(s)} \left[\ V^*_{ijt}\ |R_{ijt} = k-1, R_{ij,t-1} \leq k-2\right],
\end{aligned}$$

and, similarly, for the upper bound:

$$\mu_{k,up} = \min\left\{\mu_{k+1}, \min_s \left[\ V^*_{ijt_{ij0}(s)}\ |R_{ijt_{ij0}(s)} = k\right], \mu_{k,u1}, \mu_{k,u2}, \mu_{k,u3}, \mu_{k,u4}\right\}.$$

where

$$\begin{aligned}
\mu_{k,u1} &= \min_{t\neq t_{ij0}(s)} \left[V^*_{ijt} + \delta_{k\downarrow}\ |R_{ijt} = R_{ij,t-1} = k\right], \\
\mu_{k,u2} &= \min_{t\neq t_{ij0}(s)} \left[\ V^*_{ijt}\ -\delta_{k\uparrow}|R_{ijt} = k, R_{ij,t-1} = k-1\right], \\
\mu_{k,u3} &= \max_{t\neq t_{ij0}(s)} \left[\ V^*_{ijt}\ |R_{ijt} = k, R_{ij,t-1} \geq k+1\right], \\
\mu_{k,u4} &= \max_{t\neq t_{ij0}(s)} \left[\ V^*_{ijt}\ |R_{ijt} = k, R_{ij,t-1} < k-1\ ,\right].
\end{aligned}$$

5. The conditional distributions of the latent variables V^*_{ijt} are truncated normal. Giving our valuation model in Section 2, conditional on data and other information, the conditional distributions of V^*_{ijt} at the initial period $t_{ij0}(s)$ are given by

$$V^*_{ijt_{ij0}(s)} \sim N\left(\underline{X}'_{ij}\underline{\beta}, \frac{1}{1-\rho^2}\right), \text{ truncated by } [\mu_{R_{ijt_{ij0}(s)}}, \mu_{R_{ijt_{ij0}(s)}+1}]. \tag{10}$$

For subsequent periods, i.e., $t \in \{t_{ij0}(s)+1, \cdot\cdot\cdot, t_{ij*}(s), s = 1, \cdot\cdot\cdot, n_{ij}\}$, notice that $V^*_{ijt} = \rho V^*_{ij,t-1} + \left(X'_{ijt} - \rho X'_{ij,t-1}\right)\beta + \varepsilon_{ijt}$, the conditional distributions of V^*_{ijt} are truncated normals with means $\rho V^*_{ij,t-1} + \left(X'_{ijt} - \rho X'_{ij,t-1}\right)\beta$ and unit variance, truncated at $[\mu_{t,low}, \mu_{t,upp}]$, where

$$\begin{aligned}
\mu_{t,low} &= 1(R_{ijt} = R_{ij,t-1}+1)(\mu_{R_{ijt}} + \delta_\uparrow) + 1(R_{ijt} = R_{ij,t-1})(\mu_{R_{ijt}} - \delta_\downarrow) \\
&\quad +1(R_{ijt} \leq R_{ij,t-1} - 1 \text{ or } R_{ijt} > R_{ij,t-1}+1)\mu_{R_{ijt}}\ ,
\end{aligned}$$

$$\begin{aligned}\mu_{t,upp} &= 1(R_{ijt}=R_{ij,t-1})(\mu_{R_{ijt}+1}+\delta_{\uparrow})+1(R_{ijt}=R_{ij,t-1}-1)(\mu_{R_{ijt}+1}-\delta_{\downarrow})\\ &\quad +1(R_{ijt}<R_{ij,t-1}-1 \text{ or } R_{ijt}\geq R_{ij,t-1}+1)\mu_{R_{ijt}+1}\,.\end{aligned}$$

Fix a draw q, and denote the conditional distribution of, say, V conditional on θ as $p(V|\theta)$, where the conditioning on X and R is suppressed. After each draw of a new value of a parameter, the corresponding subvector of previous values is replaced by the new subvector that has the new value rather than the old one. We then continue to draw a new value of another parameter. Denote the q^{th} updated vector by $(\theta^{(q)}, V^{(q)})$, we repeat this P times, and as $P \to \infty$, the distribution of $(\theta^{(P)}, V^{(P)})$ converges to the distribution of (θ, V). More specifically,

1. Draw $V^{(q)}$ from $p(V|\theta^{(q-1)})$, i.e., $p(V|\beta^{(q-1)}; \mu_j^{(q-1)}; \delta^{(q-1)}; \rho^{(q-1)})$
2. Draw $\beta^{(q)}$ from $p(\beta|V^{(q)}; \mu_j^{(q-1)}; \delta^{(q-1)}; \rho^{(q-1)})$
3. Draw $\mu_j^{(q)}$ $j = 3, 4, 5$, from $p(\mu|V^{(q)}; \beta^{(q)}; \delta^{(q-1)}; \rho^{(q-1)})$. This is done by the following 3 steps:
   (a) draw $\mu_3^{(q)}$ from $p(\mu_3|V^{(q)}; \beta^{(q)}; \mu_4^{(q-1)}, \mu_5^{(q-1)}; \delta^{(q-1)}; \rho^{(q-1)})$.
   (b) draw $\mu_4^{(q)}$ from $p(\mu_4|V^{(q)}; \beta^{(q)}; \mu_3^{(q)}, \mu_5^{(q-1)}; \delta^{(q-1)}; \rho^{(q-1)})$.
   (c) draw $\mu_5^{(q)}$ from $p(\mu_5|V^{(q)}; \beta^{(q)}; \mu_3^{(q)}, \mu_4^{(q)}; \delta^{(q-1)}; \rho^{(q-1)})$.
4. Draw $\delta^{(q)}$ from $p(\delta|V^{(q)}; \beta^{(q)}; \mu_j^{(q)};\ \rho^{(q-1)})$. For example, if $\delta = (\delta_{\uparrow}, \delta_{\downarrow})$, this is done by the following 2 steps:
   (a) Draw $\delta_{\uparrow}^{(q)}$ from $p(\delta_{\uparrow}|V^{(q)}; \beta^{(q)}; \mu_j^{(q)}; \delta_{\downarrow}^{(q-1)}; \rho^{(q-1)})$.
   (b) Draw $\delta_{\downarrow}^{(q)}$ from $p(\beta|V^{(q)}; \beta^{(q)}; \mu_j^{(q)}; \delta_{\uparrow}^{(q)}; \rho^{(q-1)})$.
5. (5) Draw $\rho^{(q)}$ from $p(\rho|V^{(q)}; \beta^{(q)}; \mu_j^{(q)}; \delta^{(q)})$
6. Set $q = q + 1$, and repeat the above steps.

In practice, we discard the first M draws (in our empirical analysis, we set $M = 50,000$), and the simulated values of $(\theta^{(q)}, V^{(q)})$ from $q = M + 1, \cdots, M + Q$, can be regarded as an approximate simulated sample. The posterior expectation of a function of the parameters, $h(\theta)$, can then be estimated by the sample average

$$\frac{1}{Q}\sum_{q=M+1}^{M+Q} h(\theta^{(q)}).$$

Once we have a set of reasonable initial values, to ensure that we sample from the stationary distribution for the parameter estimates, we discard the initial $50,000$ iterations,[36] and keep the next $150,000$ iterations as sample draws. To test the null hypothesis that the Markov chain of each parameter estimate is from the stationary distribution, we use Geweke's (1992) convergence diagnostic, which tests that the means of the first 10% of the Markov chain (observations $50,001-65,000$) and the last 50% of observations are equal. The data easily pass this convergence check. We also visually check the trace plots of each Markov chain to confirm that it has a relatively constant mean and variance. Parameter estimates are then given by their sample averages. The appendix provides more details on estimation procedures.

Goodness of Fit. We use the Brier Score (Brier, 1950) and Bayes factor to compare goodness of fit of different model specifications. The Brier score is the mean squared deviation between the observed outcome and the (in-sample) predicted probability of a recommendation:

$$S = \frac{1}{\#obs} \sum_{ijt} \left[I(R_{ijt}) - \widehat{\pi}(R_{ijt}) \right]^2 ,$$

where $I(R_{ijt})$ is an indicator function, equal to one if recommendation R_{ijt} is observed, and zero otherwise; $\widehat{\pi}(R_{ijt})$ denotes the *in-sample estimate* of the probability of recommendation R_{ijt}; and $\#obs$ is the total number of recommendations issued in our sample. The Brier score penalizes large deviations in a probability forecast: the smaller is S, the better is the model fit. A perfect probability forecast would yield a Brier score of zero.

More formally, we employ the Bayes factor to assess the goodness of model fit. All specifications considered in our study are nested in the full model. We have no prior belief over the null model and the alternative (i.e., $\Pr(M_0) = \Pr(M_A) = 0.5$). Given the observed data, D, the Bayes factor, B, is defined as

$$B = \frac{\Pr(D|M_A)}{\Pr(D|M_0)},$$

where $\Pr(D|M_0)$ and $\Pr(D|M_A)$ are the marginal likelihoods of the null and alternative models, respectively. In terms of the logarithm of models' marginal likelihoods (reported in Table 4), the Bayes factor is $\exp(\log(\Pr(D|M_A)) - \log(\Pr(D|M_0)))$. Kass and Raftery (1995) argue that a Bayes factor of $2\log(B)$ that exceeds 10 ($\approx B > 150$) represents decisive evidence in favor of the alternative model against the null. A Bayes factor that exceeds $1,000$ ($B > 1000$) provides conclusive support for forensic evidence in a criminal trial (Evett, 1991). The Bayes factor also penalizes overfitting (over-parametrization) of an alternative model.

[36] Prior to identifying a set of reasonable starting values, we discarded as many as 200,000 observations.

Appendix B: variable definitions

We construct several variables from CRSP. Omitting analyst and firm subscripts (i and j), and the subscript t for the *calendar* month in which recommendation R_{ijt} is issued, we use:

ret_{-1}: stock excess return (on the market) in the past month (month $t-1$).

$ret_{-2:-6}$: median-term monthly excess return.

$ret_{-7:-12}$: long-term monthly excess return.

To preclude the impact of recommendations on stock performance (reverse-causality), returns are calculated as the holding period return based on monthly closing stock prices.Thus, $ret_{-2:-6}$ is the return received from holding a stock at the closing price in month $t-7$ and selling it at the closing price in month $t-2$.

$\sigma_{-1:-6}$: past six-month stock return volatility (daily return volatility times the square root of the number of trading days over the past six months).

$\log(turnover_{-1:-6})$: log of (trading volume in past 6 months scaled by shares outstanding).

$\log(MktCap_{-1:-6})$: log of a firm's market capitalization (monthly closing price times shares outstanding).

$Firm\_Age$: years a firm has been in the CRSP database at the calendar year of month t.

Firm accounting variables come from Compustat. Here q denotes the most recent *fiscal* quarter for which an earnings announcement was made prior to or within a calendar month t.

SUE: standardized unexpected earnings. $SUE = (EPS_q - EPS_{q-4})/std(EPS_{q:q-7})$, where $EPS_q - EPS_{q-4}$ is a firm's unexpected quarterly earnings per share and $std(EPS_{q:q-7})$ is the firm's earnings volatility over the eight preceding quarters. We require a firm to report EPS at least four times in the past eight quarters to calculate earnings volatility. The value of SUE is carried over the following quarter after the release of EPS_q.

D_{EA}: Month dummy indicating an earnings announcement was made in that month, or in the last five trading days of the previous month (to give the market time to assesse earnings).

BM: ratio of book equity to market equity in quarter q;

EP: earnings-to-price ratio. $EP = \sum_{i=0}^{3}(EPS_{q-i})/Prc_q$, where Prc_q is the stock price at the end of quarter q.

SG: annual sales growth rate. $SG = \sum_{i=0}^{3} Sales_{q-i}/\sum_{i=0}^{3} Sales_{q-4-i}$, where $Sales$ is a firm's quarterly total sales.

ROA: return on assets. $ROA = \sum_{i=0}^{3} Income_{q-i}/AT_q$, where $Income$ and AT are quarterly net income and the end-of-quarter total assets.

The I/B/E/S recommendation file yields the following analyst-related variables:

$\log(num\_anal)$: logarithm of the number of analysts with recommendations on a firm in month $t-1$.

$HSize$: logarithm of the number of analysts at a brokerage issuing stock recommendations over the course of one calendar year, as in Agrawal and Chen (2008).

We use the I/B/E/S Detail History and Summary Statistics files to construct:

$FRtoP$: Earnings forecast revisions to price ratio is the rolling sum of the preceding six months revisions to price ratios (Jegadeesh et al., 2004). $FRtoP = \sum_{i=1}^{6}(f_{t-i}-f_{t-1-i})/Prc_{t-1-i}$, where f_t is the mean consensus analyst quarterly forecast in month t.

$CFtoP$: Consensus quarterly earnings forecast to price ratio. $CFtoP = f_{t-1}/Prc_{t-1}$.

$FDisp$: Forecast dispersion is the standard deviation of analysts' quarterly earnings forecasts at month $t-1$ scaled by Prc_{t-1}.

$FDev$: Analyst earnings forecast deviation is the difference between an analyst's forecast and the consensus earnings forecast at month $t-1$ scaled by Prc_{t-1}.

Finally, we consider:

IH: Institutional Holdings is the percentage of a firm's equity held by institutional investors in quarter q, obtained from 13f quarterly filings to the Securities and Exchange Commission (Thomson Financial 13f institutional database).

D_{IB}: Dummy variable indicating an investment banking relationship (lead- or joint-management appointment) in the previous five years between the analyst's brokerage house and the firm. We obtain all US debt and equity offerings from the Security Data Company (SDC) Database.

$\log(year\_brkg)$: Logarithm of the years an analyst has been at his/her current brokerage firm.

$\log(year\_IBES)$: Logarithm of the years an analyst has been in the I/B/E/S database.

Table 12 provides summary statistics for these public information variables in the three-tier sample. The right-most column reports results of univariate comparisons of means between stocks with Sell and Buy recommendations. All differences in control variables between sell and buy recommendations are significant at a 5% significance level.

Table 12: Descriptive Statistics for Firm and Analyst-related Variables

	Mean	Std. Dev.	$Quar_1$	$Quar_2$	$Quar_3$	Buy−Sell
ret_{-1}	0.750	11.078	−5.405	0.746	6.879	0.486***
$ret_{-2:-6}$	3.813	22.913	−9.584	3.268	15.882	2.602***
$ret_{-7:-12}$	4.492	26.689	−10.925	3.745	18.316	6.265***
$\sigma_{-1:-6}$	25.554	13.360	15.862	22.242	31.352	−2.212***
$\log(turnover_{-1:-6})$	−0.164	0.735	−0.641	−0.137	0.344	−0.041***
$\log(MktCap_{-1:-6})$	14.413	1.552	13.271	14.306	15.459	−0.104***
$\log(num\_anal)$	2.644	0.689	2.197	2.708	3.135	0.058***
$HSize$	3.742	1.113	3.178	3.951	4.673	−0.226***
SUE	0.330	1.451	−0.692	0.359	1.553	0.426***
BM	0.516	0.345	0.272	0.443	0.673	−0.098***
EP	0.017	0.109	0.018	0.043	0.064	0.025***
SG	1.115	0.212	0.999	1.089	1.199	0.057***
ROA	0.062	0.112	0.015	0.062	0.123	0.026***
$FAge$	22.364	18.774	9	16	32	−0.286**
$FRtoP$ ($\times 10^{-3}$)	−0.652	12.586	−2.951	0.605	3.435	2.489***
$CFtoP$ ($\times 10^{-2}$)	1.005	1.548	0.649	1.209	1.738	0.362***
$FDisp$ ($\times 10^{-2}$)	0.195	0.307	0.038	0.083	0.201	−0.096***
$FDev$ ($\times 10^{-3}$)	−0.103	4.898	−1.056	0	1.107	0.612***
IH	0.747	0.241	0.609	0.790	0.919	0.032***
$\log(year\_brkg)$	1.487	0.677	1.099	1.609	1.946	−0.091***
$\log(year\_IBES)$	1.893	0.589	1.386	1.946	2.398	−0.029***

Results of univariate comparisons of means between stocks with a Sell (Sell or Strong Sell) recommendations and those of Buy (Buy and Strong Buy) are reported in the far right column. *** and ** denote statistical significance at 1% and 5% levels.