Buy-side Analysts, Sell-side Analysts and Private Information Production Activities

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Abstract

This paper models the effect of coverage initiation by a sell-side analyst on the production of private information. It shows that the sell-side analyst’s information production may crowd out information production by buy-side analysts. Nonetheless, coverage initiation increases the total amount of private information that is available to institutional investors. Coverage initiation may result in greater losses sustained by liquidity traders and lower information gathering costs in the economy. Investment banking relationships within a brokerage house stimulates information production by the sell-side analyst. Prohibiting such relationships may decrease the overall amount of information available to institutional investors and price efficiency.
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1. INTRODUCTION

The burst of the Internet bubble and the spate of accounting scandals that followed led many commentators and regulators to question the role of sell-side analysts in the supply of investment advice. Sell-side analysts who are employed by brokerage houses and their investment banking divisions have been criticized for failing to predict companies’ (mis)fortunes. The public scrutiny championed by Eliot Spitzer, New York State’s attorney-general, has also spurred renewed interest in the special relationship between sell-side analysts and institutional investors, their major commercial clients and its effect on, lesser informed, individual investors.

Institutional investors conduct their own independent research in addition to acquiring investment advice from sell-side analysts. Being sophisticated investors, one would expect them to be less vulnerable to flaws in sell-side analysts’ advice.\(^1\) To see whether or not this is the case, this paper develops an analysis of the nature of the interaction between sell- and buy-side analysts in information production activities. Specifically, this paper investigates how information acquisition activities by buy-side analysts (i.e., institutional investors) are affected by coverage initiation on the part of a sell-side analyst, and how information production is shared between sell-side and buy-side analysts.\(^2\) This analysis contributes to the literature and to the on-going debate about the relative role of sell-side analysts as providers of equity research by showing that coverage initiation by a sell-side analyst, while working to increase overall amount of private information, also reduces information production on the part of buy-side analysts.

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\(^1\) Indeed, regulators seem to emphasize the damage sustained by individual investors who rely on sell-side analysts’ recommendations as opposed to the losses sustained by institutional investors.

\(^2\) The need to develop such theory is well acknowledged in the literature (see Core, 2001).
That is, in equilibrium the bulk of private information is produced by the sell-side analyst. Thus, coverage initiation by a sell-side analyst has a critical impact on institutional investors’ profits and asset prices.

More broadly, the paper investigates three measures that capture the effect of the interaction among professional security analysts in the production of equity research on the information environment in the marketplace: total amount (or, alternatively, precision) of private information available to investors prior to corporate disclosures, market liquidity (or, price sensitivity to investors’ demand), and price efficiency. I focus on these measures because they are associated with the degree of information asymmetry between market makers and informed investors.

I develop a stylized model in which costly information production is initially carried out only by buy-side analysts. After analyzing the properties of the equilibrium in this benchmark setting, a second setting is examined in which a sell-side analyst is introduced. This model corresponds to the launching of firm coverage by a sell-side analyst. What distinguish a sell-side from a buy-side are three important features. First, the sell-side and buy-side face different incentives to collect private information. The buy-side is interested in maximizing profit from informed speculation. The sell-side, in contrast, attempts to generate trading commissions paid by institutional investors. Second, the sell-side analyst avails his information to a number of users. Buy-side analysts do not share their information with each other. Third, the sell-side has the specialized capacity to enhance trading activity in a firm’s stock by attracting more liquidity traders (who can be thought of as unsophisticated individual investors).

\[\text{Recent evidence by Irvine (2000) confirms the conventional wisdom on Wall Street whereby sell-side analysts’ research generates incremental commission income for their brokerage firms.}\]
The first important finding of the paper is that coverage initiation by a sell-side analyst has two conflicting effects on the incentive of buy-side analysts to collect costly private information. First, since coverage initiation involves more liquidity trading, the overall profit available to informed traders is higher. This prompts buy-side analysts to produce more information. Second, the availability of the sell-side analyst’s information to the buy-side reduces his incentive to collect information on his own. Notwithstanding this second effect, the initiation of sell-side analyst coverage tends to increase the precision of institutional investors’ information.

The second important finding is the effect of commissions on institutional investors’ trading aggressiveness. At the trading stage, the commission paid by institutional investors to the brokerage house works to reduce the profit on the marginal share traded. As a result, investors trade less aggressively after coverage initiation, everything else being equal. This lower trading aggressiveness also has important implications for market liquidity and price efficiency. Specifically, market liquidity is negatively related to the precision of private information. This, in turn, suggests the possibility of lower liquidity (i.e., the price being more sensitive to demand) following coverage initiation by a sell-side analyst. Therefore, the market will be more liquid after coverage initiation provided the increase in liquidity trading activity brought about by the sell-side analyst is sufficiently high. An additional important consequence of the effect of trading commissions on trading aggressiveness is that price efficiency may be lower after coverage initiation by the sell-side analyst.

The third important finding concerns the effect of investment banking activity on the sell-side analyst’s information collection activity. Considering this is important in light of the recent
public scrutiny mentioned earlier.\textsuperscript{4} In economic terms, investment-banking relationship can be thought of as a subsidy to the cost of equity research that is paid by the investment banking business. I show that this subsidy stimulates the sell-side analyst to produce a more precise signal and therefore to increase the overall amount of private information. This, in turn, has two implications. First, because more precise private information leads to greater losses on part of uninformed investors, the analysis is consistent with the notion that investment-banking relationship adversely affects small individual investors. Second, buy-side analysts would collect less information on their own the higher the subsidy. This implies that institutional investors become more dependent on the sell-side analyst’s signal. Thus the investment advice of a sell-side analyst has a more substantial impact on institutional investors’ profits as well as on asset prices. This also implies that markets are more susceptible to errors in sell-side analysts’ forecasts and recommendations when equity research is influenced by investment banking activity.

The next section presents and analyzes the benchmark setting in which buy-side analysts trade only on own-produced information. Section 3 introduces into the model a sell-side analyst and examines properties of the information environment in which information acquisition activities are undertaken by both sell-side and buy-side analysts. Section 4 analyzes the effects of coverage initiation by comparing the total amount of private information, market liquidity and price efficiency across the two settings. The investment banking relationship and its ramifications are investigated in Section 5. Empirical implications and relation to existing theoretical research are discussed in Section 6 while a summary is offered in Section 7.

\textsuperscript{4} In this analysis I ignore any systematic bias that is incorporated into the sell-side recommendations for reasons detailed later in the paper.
2. BENCHMARK SETTING: OWN INFORMATION PRODUCTION

This section presents the economic setting and then derives various results that will furnish the platform for subsequent references and comparisons. Two sets of results are discussed. First, for the case where precision of private information is exogenous and then for the case where information production activity is endogenous.

2.1 ECONOMIC SETTING

Consider a three-date securities market with a risky and a risk-free asset available for investment. Without loss of generality the risk-free rate is set equal to zero. The risky asset’s end-of-period value, denoted by \( v \), is normally distributed with mean zero and variance \( 1/a \) (that is, a precision of \( a \)). In this market there are two types of investors: informed buy-side analysts and uninformed (i.e., liquidity) traders. The timeline is as follows. At the beginning of the first period, date 1, investors carry out, simultaneously and independently, information collection activities. They trade on their private signal at date 2. At date 3 the value of \( v \) becomes publicly observable.

A buy-side analyst’s date 2 information set consists of an idiosyncratic piece of information, \( z_i \), where:

\[
z_i = v + \varepsilon_i. \tag{1}
\]

That is, \( z_i \) is a noisy signal of the forthcoming public signal \( v \). The noise term, \( \varepsilon_i \) is normally distributed with mean zero and variance \( 1/d_i \) and is independent of \( v \). Denote by \( g_i \) the ratio \( d_i/(a+d_i) \). This ratio reflects the weight an informed investor places on his private signal in the
estimation of \( v \). As the precision of the private signal, \( d_i \), approaches infinity, \( g_i \) tends to one and the private signal converges to \( v \). In contrast, as \( d_i \) approaches zero, \( g_i \) goes to zero as well because the signal becomes pure noise.

This securities market is populated by \( M \) buy-side analysts, each employed by a single institutional investor. I therefore refer to buy-side analysts and the employing institutional investors interchangeably. Each institutional investor places an order for \( x_i \) shares at date 2. Also at that date, liquidity traders submit orders for \( x_u \) shares, where \( x_u \) is normally distributed with mean zero and variance \( 1/u \), and is independent of all other random variables. The date 2 net order flow, denoted by \( w \), is thus given by:

\[
w = \sum_{i=1}^{M} x_i + x_u. \tag{2}
\]

There also exists a risk-neutral and perfectly competitive market maker who sets the market price at date 2, \( P_2 \), at which she absorbs this net order flow. As in Kyle (1985), the price set is equal to \( \mathbb{E}(v|w) \), the expectation of \( v \) conditional on the market maker’s observation of \( w \).

### 2.2 Equilibrium with Exogenous Information Acquisition

In this section I derive a linear equilibrium for a market in which idiosyncratic private information is exogenous and of the same precision. Some basic properties of the equilibrium are subsequently established as these will turn out to be useful for the understanding of the endogenous case.
With exogenous information, the only decision each buy-side analyst needs to make concerns his date 2 demand, $x_i$. The number of shares traded by the buy-side analyst should maximize his long-term expected profits, $E_i(\pi_i)$, conditional on the observed signal $z_i$. That is, the $i$th analyst’s maximization problem is

$$\max_{x_i} E(\pi_i \mid z_i) = E((v - P(x_i))x_i \mid z_i).$$  

(3)

It is assumed and later verified that

$$x_i = \alpha z_i,$$  

(4)

and,

$$P_2 = \lambda w.$$  

(5)

where (i) $x_i$ maximizes expression (3) subject to the conjecture that the date 2 price is given by (5) and (ii) the date 2 price is equal to $E(v \mid w)$, where $w$ is given by expression (2). In determining the price, the market maker conjectures that informed demand is given by (4). The parameter $\alpha$ reflects the aggressiveness with which an informed investor trades on his private information. The parameter $\lambda$ represents the inverse of market depth, as it measures the sensitivity of the market price to the order flow. The greater is the market depth, the less does demand affect price.

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5 I do not consider the cost associated with executing the trade. This cost is set to zero without loss of generality.
Lemma 1 characterizes the Date 2 equilibrium in the benchmark setting with exogenous information.

**Lemma 1**

*In the benchmark setting, a linear market equilibrium exists at date 2. In this equilibrium,*

\[
\alpha = \sqrt{\frac{ga/u}{M}},
\]

(6)

and,

\[
\lambda = \frac{\sqrt{Mgu/a}}{[2 + (M - 1)g]}. \tag{7}
\]

**Proof:** See the Appendix.

The more precise the private signal is with respect to the final liquidation value, the more aggressively would an informed investor trade on his information. Hence the positive relation between \(\alpha\) and \(g\) (and \(d\)) that is captured in Eq. (6). More intense competition among institutional investors, as implied by a larger \(M\), will reduce the return to private information. Thus, \(\alpha\) is inversely related to \(M\).

With exogenous information, the only two relevant measures of the information environment in the pre-disclosure period to be investigated here are \(\lambda\), the market depth parameter, and price efficiency. I begin by examining the effects of an increase in the precision of private information, \(d\), and the number of informed traders, \(M\), on the market depth parameter. Proposition 1 follows from straightforward differentiation of Equation (7).
Proposition 1

(i) When $M > 3$ the market depth parameter, $\lambda$, is initially increasing in the precision $d$, reaching a maximum at $d=2a/(M-3)$ and then decreasing. Otherwise, it is monotonically increasing in $d$.

(ii) The market depth parameter, $\lambda$, is initially increasing in the number of informed investors, $M$, reaching a maximum at $M=1+2(a/d)$ and then decreasing. In the limit, as $M \to \infty$, $\lambda \to 0$.

The first part of the proposition states that $\lambda$ is potentially unimodal in the precision of the private signal $d$. This is because an increase in $d$ has two effects on $\lambda$. First, holding informed investors’ trading aggressiveness fixed, a more precise private signal implies larger information asymmetry between the market maker and informed investors. This, in turn, will prompt the market maker to price-protect herself by increasing $\lambda$. However, a higher precision of the private signal also leads investors to trade more aggressively, resulting in a larger portion of their private information being incorporated into the order flow (information leakage effect). This mitigates the adverse selection problem faced by the market maker, implying a lower $\lambda$. When $d$ is relatively small or when $M \leq 3$, the first force will dominate. However, when $d$ is sufficiently large any further gain in the precision of the private signal will have only a small effect on the individual investor’s information advantage, but a greater leakage effect, implying an overall reduction in $\lambda$. Turning to the effect of $M$ on $\lambda$, note that increased competition (i.e., a higher $M$) erodes investors’ information advantage, again due to the leakage effect. On the other hand, the marginal investor entering the market employs an additional piece of information that is orthogonal to other investors’ information. This added information asymmetry will then prompt
the market maker to price-protect herself by increasing $\lambda$. Though the effect of competition is relatively small initially, it dominates when $M$ is large enough, at which point $\lambda$ will start to decline in $M$. In the limit, competition becomes so intensive enabling the market maker to extract all private information from the order flow. Therefore, in the limit $\lambda$ goes to zero.

The second measure pertaining to the nature of the information environment in the pre-disclosure period is price efficiency (or, alternatively, price informativeness). The analytical construct that measures price efficiency is the variance of the true value, $v$, conditional on the net order flow, $w$. The more information is incorporated into price, the lower the conditional variance. Formally, this measure, denoted by $I$, is calculated as

$$I = \frac{1}{a} \left[ \frac{2a + d}{2a + (M+1)d} \right].$$

(8)

It is straightforward to show that $I$ is decreasing in both $d$ and $M$. That is, price informativeness increases with the precision of the private signals and the intensity of competition among informed investors. This is intuitive as more accurate private signals also imply that the order flow, and therefore price, is also more informative. In addition, more competition among informed traders results in a larger portion of the private signal being incorporated into price than with fewer traders.

2.3 EQUILIBRIUM WITH ENDOGENOUS INFORMATION ACQUISITION

In this setting each buy-side analyst makes two sequential decisions. First, prior to trading (i.e., at date 1), the buy-side analyst optimally chooses the precision of his signal, $d_i$. 
Then, at date 2, taking as given the precision of the signal produced at date 1, each analyst selects the number of shares to trade, as in the exogenous case. The solution to this sequence of events involves backward induction decision process. Let \( \pi_i \), denote the ex-ante profit at date 1. This is equal to the expected trading profit less the cost of information acquisition activity. Assuming quadratic cost function with (marginal) cost parameter \( c \), the optimal precision, \( d_i \), will maximize

\[
\max_{d_i} \pi_i = \int \pi_i^* d\xi_i - 0.5cd_i^2,
\]

where \( \pi_i^* \) denotes the investor’s expected trading profits at date 2. Note that any generic cost function \( C(d_i) \) that satisfies \( C'(d_i)>0 \) and \( C''(d_i)\geq0 \) would work to ensure a unique solution to the investor’s information collection problem. However, to enhance the model’s tractability, I specifically assume that \( C(d_i) = 0.5cd_i^2 \) for some scalar \( c, c > 0 \). Under this cost structure, precise information is costly to produce and the marginal cost is non-negative.

Since each buy-side analyst conducts his information search privately, neither the market maker nor any other buy-side analyst can observe the chosen precision. This implies that at the first stage of the game, each analyst’s choice will be a function of his conjecture of other analysts’ optimal choice as well as of the market maker’s \( \lambda \). That is, each buy side analyst will not internalize the effect of his precision choice on either other analysts’ choice or on \( \lambda \). In the Appendix (Proof of Proposition 2) it is shown that the ex-ante expected net profit function maximized by each buy-side analyst is given by

\[
\max_{d_i} \pi_i = \int \pi_i^* d\xi_i - 0.5cd_i^2
\]
\[
\max_{d_i} \pi_i \equiv E(\pi^*_i) - 0.5cd_i^2 = \frac{g_i}{a} \left(\frac{1 - \lambda(M - 1)\alpha_j}{4\lambda}\right)^2 - 0.5cd_i^2, \tag{10}
\]

where \(\alpha_j\) represents \(i\)th analyst’s conjecture of other investors’ trading aggressiveness. Consistent with the assumption of non-observable choices, the optimal precision is calculated by differentiating Eq. (10) with respect to \(d_i\) while holding \(\alpha_j\) and \(\lambda\) fixed. The resulting first order condition is set to zero, \(d_i\) is then equalized across all investors (i.e., \(d_i = d\) for all \(i\)) while \(\lambda\) is substituted for by using Eq. (7). Analysis of the equilibrium \(d\) yields two intuitive results concerning the overall amount of private information: First, the precision of the private signal is negatively related to the cost parameter \(c\), and second, it is decreasing in the number of informed investors.

Using these findings I now turn to explore the implications for the other two measures of the information environment in the marketplace: the depth parameter and price efficiency.

**Proposition 2**

When information acquisition is independently carried out by each buy-side analyst

(i) The depth parameter, \(\lambda\), is unimodal in the cost parameter \(c\), first increasing, and then decreasing after reaching a maximum (for \(M > 3\)).

(ii) The sign of the derivative of the depth parameter with respect to \(M\) is ambiguous.

(iii) Price efficiency is monotonically decreasing (increasing) in the cost parameter (the number of informed investors).

**Proof:** See the Appendix
The first part of the proposition holds because $c$ and the precision of the private signal are negatively related implying that as $c$ increases $d$ becomes smaller. The unimodality of $\lambda$ in $d$ that was discussed in the exogenous case suggests that as information acquisition activity becomes more costly, the depth parameter will initially increase, but then decrease, as the private signal becomes sufficiently inaccurate. With respect to the second part of the proposition, note that there are two effects on $\lambda$ as $M$ increases. The first is the direct effect on the depth parameter that is present with exogenous information. The second is an indirect effect owing to the fact that $d$ decreases as $M$ increases. However, since the depth parameter is unimodal in both $M$ and $d$ the net effect could be of either sign. The last part of the proposition states that price efficiency will be negatively related to information acquisition costs. This is intuitive given that $d$ is inversely related to $c$. In contrast, the relation between price informativeness and the number of informed investors, $M$, is positive, notwithstanding the fact that $d$ and $M$ are negatively related in equilibrium. This is because the direct effect of $M$ on price efficiency is larger than the indirect effect of $M$ on price efficiency through its effect on $d$.

3. INITIATION OF FIRM COVERGAE BY A SELL-SIDE ANALYST

In this section a sell-side analyst is introduced into the model. I first describe how the basic setting is consequently altered. As will be seen shortly, one important component of the setting analyzed here is the modeling of trading commissions as a mechanism through which the sell-side analyst is compensated for his costly research activity. The analysis then proceeds to explore the economy with exogenous information before considering endogenous information gathering activities.
3.1 ECONOMIC SETTING

Consider again the benchmark setting. Let us now modify it to include a full-service broker, or alternatively, a sell-side analyst whose objective is to collect and sell information to clients in order to generate trading commissions. The timeline in this setting is as in the benchmark case modified as follows. Information acquisition activities are taking place simultaneously at date 1 by the sell-side and all buy-side analysts. At date 2, the broker and each investor negotiate the commission rate and number of shares to be traded through the full-service broker. At this stage the broker and each client learn about the quality of their respective information. At date 3, trading takes place and trading commissions are paid to the broker. Finally, at date 4, the value of \( v \) becomes publicly observable.

In the presence of the sell-side analyst, buy-side analysts will have access to the broker’s information in addition to their own information. While clients do not pay directly for the sell-side analyst’s information, they direct some or all of their demand through the full-service brokerage house. This entails incurring trading commissions that are typically higher than those charged by discount brokers by a margin that compensates the full-service broker for his costly information gathering activities.\(^6\) More specifically, the commission paid by clients is assumed to be related to the number of shares traded through the full-service broker. Since brokers cannot force clients to trade the full amount of shares that their investment advice generates, each investor may decide to channel only a fraction of his market order through the full-service broker. Let this fraction be denoted by \( q \) and let the commission rate be denoted by \( t \). For equilibrium with trading commissions to exist it is required that \( q \) is strictly positive. I assume

\(^6\) Commissions charged by the discount broker are normalized to zero without loss of generality. Commissions
that the broker’s commission revenue function, denoted by $R$, is quadratic in the number of shares traded via the broker. This assumption is used to maintain tractability of the model. Similar approach is taken, for example, in Subrahmanyam (1998) and Dow and Rahi (2000). As is discussed below, the commission rate $t$ is optimally chosen by the sell-side analyst to maximize his revenues. Without imposing further restrictions on the broker’s choice of the commission rate, certain values of $t$ may lead to a reduction in buy-side analysts’ profits, potentially implying non-existence of equilibrium that otherwise would involve higher total available profits (i.e., the sum of expected profits across buy-side analysts and the sell-side analyst) than the benchmark setting. This, in turn, will imply that $t$ is not a continuous function in exogenous variables. It is therefore assumed that in such cases the sell-side analyst will make a transfer of $F$ dollars to the buy-side analyst to make him willing to trade with the brokerage house. While this assumption simplifies the analysis, this feature of the economic setting has an additional merit in that it is consistent with the real-world practice of soft-dollars. This practice involves provision of non-execution services (as well as direct payments) by brokerage houses to large institutional clients in exchange for directed trades. In effect this arrangement works to reduce the amount paid by clients in trading commissions.\(^7\)

It is also assumed that market participants cannot observe whom the broker is informing. Note that the trading strategy of the $i$th investor therefore will not be affected by the decision of the $j$th investor to use the full-service broker, as this action is not publicly observable. However, investors will employ some conjectures as to how many clients the broker has informed. That the information transmission between the broker and clients is unobservable also implies that the

\(^7\) See Blume (1993) for a fuller description of soft-dollars arrangements.
broker will always want to inform as many buy-side analysts as possible.\textsuperscript{8} In equilibrium, buy-side analysts will correctly conjecture that the broker behaves in this fashion.

As was discussed in the Introduction, one important effect of the broker’s coverage initiation is that his marketing activities work to increase the level of liquidity by attracting small individual investors who are less informed than buy-side analysts. Being small “players” they are not privileged to the same level of tailored advice as institutional clients. This is operationalized by assuming that the investment advice they get is already in the public domain and is thus worthless. These small investors are therefore modeled as liquidity traders. It is further assumed that they do not pay for investment advice, as institutional investors do.\textsuperscript{9} The above discussion implies that in a market populated by $M$ buy-side analysts the sell-side analyst will generate

$$R = \sum_{i=1}^{M} t(qx_i)^2 - MF$$

in (net) commission revenues.

To focus attention on the impact of the sell-side analyst’s information collection and dissemination activities, and to further simplify the exposition, it is assumed that the broker does not trade on his own account.

It is assumed that each buy-side analyst receives an idiosyncratic signal from the sell-side analyst. This assumption reflects the view that a sell-side analyst’s main role is to serve as a conduit through which “raw” information is conveyed to clients who, in turn, use this

\textsuperscript{8}This is consistent with the findings of Bhushan (1989), O’Brien and Bhushan (1990), and Potter (1992) whereby sell-side analyst coverage is highly correlated with institutional following.
information to draw their own inferences.\textsuperscript{10} Alternatively, this can be viewed as the sell-side analyst answering client-specific questions that help buy-side analysts understand specific aspects of the sell-side analyst’s background information, assumptions and modeling techniques used in forming his investment recommendation. This assumption therefore implies that each buy-side analyst will observe two idiosyncratic signals: the first, denoted, as before, by \( z_i \), is the one generated by own information gathering activities. The second, \( s_i \), will be the one that is based on broker-supplied information. It is assumed that \( z_i = \nu + \varepsilon_{di} \) and \( s_i = \nu + \varepsilon_{si} \) where \( \varepsilon_{di} \) is normally distributed with mean zero and variance \( 1/d \), and \( \varepsilon_{si} \) is normally distributed with mean zero and variance \( 1/e \). The two error terms are assumed to be uncorrelated.

3.2 EQUILIBRIUM WITH EXOGENOUS INFORMATION ACQUISITION

In this setting, the broker will set \( t \) optimally so as to maximize his commission revenue function. Investors, on their part, will optimally choose their total order flow, and the fraction \( q > 0 \) of their overall demand which will be traded with the full-service broker. For a given \( q \) and \( t \), an informed investor’s maximization problem at the trading stage (ignoring sunk cost of information production and any soft dollar payments) can be written as

\[
\max_{\pi_i} E(\pi_i \mid z_i) = E((\nu - P(x_i))x_i \mid z_i, s_i) - t(qx_i)^2.
\]  

\textsuperscript{9} In Section 6 I discuss Easley et al (1998) who provide evidence consistent with this assumption.

\textsuperscript{10} This is consistent with the view that best analysts need not be the best stock pickers or earnings forecasters. Rather, it is their ability to obtain and convey information that other investors cannot obtain. Indeed, Institutional Investor ranks industry knowledge first and stock picking ability and accuracy of earnings forecasts eleventh and twelfth, respectively, in importance among institutions it polls.
It is assumed, and later verified, that an investor’s demand is linear in the information variables, \( z_i \) and \( s_i \) as follows:

\[
x_i = \beta z_i + \gamma s_i.
\]

Let \( h \equiv d/(a+d+e) \) and \( k \equiv e/(a+d+e) \). Then, taking \( \lambda \) and \( t \) as given, the coefficients \( \beta \) and \( \gamma \) are calculated as (see the Appendix):

\[
\beta = \frac{h}{\lambda[2 + (M - 1)(h + k)] + 2tq^2}, \tag{13}
\]

and

\[
\gamma = \frac{k}{\lambda[2 + (M - 1)(h + k)] + 2tq^2}. \tag{14}
\]

Note that for a given \( \lambda \), the client’s demand declines in the commission parameter, \( t \), and the fraction traded via the full-service broker, \( q \). The intuition is that trading commissions have a taxing effect on investors’ demand: relative to the benchmark case, the marginal unit traded delivers lower profit, implying that investors find it beneficial to trade less, all else equal.

Inserting the expressions for \( \beta \) and \( \gamma \) into the broker’s revenue function yields the expression from which the equilibrium \( t \) is later derived:

\[
R = \sum_{i=1}^{M} t(qx_i)^2 - MF = Mtq^2 \frac{(hz_i + ks_i)^2}{\{\lambda[2 + (M - 1)(h + k)] + 2tq^2\}^2} - MF \tag{15}
\]
Inspecting Eq. (15) reveals that the broker faces the following trade-off in setting the commission rate, \( t \). On one hand, a higher \( t \) implies higher revenues at any given demand level. However, as discussed shortly before, a higher \( t \) also implies that clients’ order flow will be smaller. The optimal \( t \) is such that the incremental revenue resulting from a small increase in \( t \) just offsets the effect of the decline in trading volume.

Differentiating Eq. (15) with respect to \( t \), setting the resulting expression to zero and solving for the optimal \( t \) yields:

\[
t = \frac{\lambda[2 + (M - 1)(h + k)]}{2q^2}.
\]  

(16)

Note that for a given market depth parameter, the commission rate is inversely related to the fraction of shares traded with the full-service broker \( q \). This is intuitive as the broker will charge a higher commission rate when trading volume is low, but will be willing to lower the commission rate when the volume is high. However, the product \( tq^2 \) is a constant for a given set of exogenous variables. That is, it is independent of the actual choice of \( q \). As a result, the model holds for all positive values of \( q \).

Using the definition of \( \lambda \) it is now possible to substitute Eq. (16) in the expressions derived above for \( \beta \) and \( \gamma \) to obtain the equilibrium expressions for \( \beta \), \( \gamma \) and \( \lambda \).
Lemma 2

Let $\lambda_0$ and $1/u_0$ denote the equilibrium values of the market depth parameter and variance of liquidity trading in the exogenous benchmark setting with $1/u > 1/u_0$. Then equilibrium exists in the setting with the sell-side analyst provided

$$\frac{\lambda}{u} - \frac{\lambda_0}{u_0} \geq 0.$$ 

In such equilibrium,

$$\beta = \frac{h}{\sqrt{M(h+k)[3+(M-1)(h+k)]^{\frac{u}{a}}}}, \quad (17)$$

$$\gamma = \frac{k}{\sqrt{M(h+k)[3+(M-1)(h+k)]^{\frac{u}{a}}}}, \quad (18)$$

and

$$\lambda = \frac{\sqrt{M(h+k)[3+(M-1)(h+k)]^{\frac{u}{a}}}}{2[2+(M-1)(h+k)]}. \quad (19)$$

**Proof:** See the Appendix.

For equilibrium to exist, it must be the case that expected total available profits, those of investors as well as of the sell-side analyst, are at least as large as the sum of buy-side analysts’ expected profits in the absence of the sell-side analyst. This sum is just equal to the aggregate loss sustained by noise traders. Mathematically, the product of the market depth parameter and the variance of liquidity traders’ demand represents total profits. Since the level of liquidity trading is potentially higher in the presence of the sell-side analyst, buy-side will benefit from coverage initiation to the extent that $\lambda / u - \lambda_0 / u_0 \geq 0$. This is because buy-side analysts will be
able to capture a fraction of the excess profitability and thus be better-off in an equilibrium with a sell-side analyst than in an equilibrium without him. Though with exogenous information buy-side analysts always have more information once the sell-side analyst initiates coverage, I show later (see Proposition 5 and Figure 1) that for this condition to be satisfied, the sell-side analyst must furnish buy-side analysts with information that is of sufficiently high quality. Put differently, for a buy-side analyst to “survive” he must have forecasting ability that is good enough.

In any such equilibrium investors’ trading aggressiveness is captured by $\beta$ and $\gamma$. Note that whenever $h$ and $k$ show up in Eq. (19) they do so in a particular additive form: $(h+k)$. This sum corresponds to the total precision of the two information signals that buy-side analysts observe. Using the definition of $h$ and $k$, Eq. (19) can be rewritten directly as a function the total precision as follows:

\[
\lambda = \frac{\sqrt{M(d+e)[3a+(M+2)(d+e)]}}{2[2a+(M+1)(d+e)]^\frac{1}{2}}. \tag{20}
\]

The next proposition analyzes the properties of the depth parameter.

**Proposition 3**

*In equilibrium with sell-side analyst coverage and exogenous information:*

(i) The market depth parameter, $\lambda$, is monotonically increasing in the total precision of investors’ signals $(d+e)$.
(ii) The market depth parameter, $\lambda$, is monotonically increasing in the number of informed investors, $M$. In the limit, as $M \rightarrow \infty$, $\lambda = \frac{\sqrt{u}}{2}$.

**Proof:** the proof follows from straightforward differentiation of $\lambda$.

Recall that in the benchmark setting the depth parameter was shown to be unimodal in both the precision of the private signal and the number of informed investors. This is not the case in the presence of trading commissions. The reason for this is the tax effect that commissions have on trading aggressiveness. An increase in total precision has two countervailing effects on $\lambda$, which in absence of trading commissions, lead to unimodality of the depth parameter in total precision. However, with trading commissions the balance between the positive effect on $\lambda$, due to buy-side analysts being better informed, and the negative effect on $\lambda$, owing to greater trading aggressiveness of informed investors, is changed in favor of the former. This is because as investor-clients scale back their trading aggressiveness, the degree of information leakage is reduced. As a consequence, greater precision of private information implies greater adverse selection problem on part of the market maker.

Similarly, the effect of lower trading aggressiveness is sufficiently large to prevent an increase in competition (i.e., a larger $M$) from resulting in lower $\lambda$: the marginal investor who enters the market acts on idiosyncratic piece of information, but with tempered aggressiveness due to the tax effect of commissions. This leads the market maker to price-protect against the heightened information asymmetry by gradually increasing $\lambda$ as $M$ increases. In addition, the tax effect also means that, even as the number of informed investors goes to infinity, investors maintain a degree of information advantage (that is, it is never fully eroded) to be able to pay the
commission. As a result, and in contrast to the benchmark case where $\lambda$ tends to zero when $M$ goes to infinity, the market will never be infinitely liquid.

Turning to the second measure of interest, price efficiency, the conditional variance of the true value, $v$, given the order flow, $w$, is now calculated as

$$I = \frac{1}{a} \left[ \frac{4a + (M + 2)(d + e)}{4a + 2(M + 1)(d + e)} \right].$$  \hfill (21)

It is straightforward to show that, as in the benchmark case, $I$ is decreasing in both the total precision of private information, $d + e$, and $M$. That is, price efficiency improves with these variables. However, in contrast to the benchmark case, the rate of improvement is lower here. This is because as investors act less aggressively on their private information, relatively less of it is incorporated into price as either total precision or number of informed investors increases.

### 3.3 EQUILIBRIUM WITH ENDOGENOUS INFORMATION ACQUISITION

With endogenous information acquisition, information collection takes place by both buy-side analysts and the full-service broker at date 1. The sell-side analyst’s objective is to maximize his commission revenues by choosing the appropriate level of precision given his conjecture of the precision of information each buy-side analyst collects on his own. Similarly, each buy-side analyst employs conjectures regarding other analysts’ and the broker’s information gathering activities when making his optimal decision. As before, it is assumed that the market maker cannot observe the precision of private signals. Therefore, agents do not internalize the effect of their precision choice on the market depth parameter. However, each investor knows
that the precision of his signal will become observable to the broker at a later stage; the broker also takes into account that the accuracy of his information will become known to clients at the negotiation stage at date 2. Thus, all agents do internalize the effect of their decisions on the commission rate that will be charged at date 2. In addition, the broker internalizes the impact of his decision on clients’ trading aggressiveness.

In the Appendix it is shown that, given an investor’s conjecture of other investors’ trading strategy – that is, the conjectured weights $\beta_j$ and $\gamma_j$ - the ex-ante expected net profit function maximized by each institutional investor can be expressed as

$$\max_{d_i} \pi_i = \frac{h_i + k_i}{2a} \left[ 1 - \lambda(M - 1)(\beta_j + \gamma_j) \right]^2 + F - 0.5c d_i^2,$$  \hspace{1cm} (22)

whereas the ex-ante expected net profit function maximized by the full-service broker is\(^{11}\)

$$\max_{e} \pi_b = E(R) - 0.5ce^2 = M \frac{h + k}{8a} \frac{1}{\lambda[2 + (M - 1)(h + k)]} - MF - 0.5ce^2.$$

\hspace{1cm} (23)

Note that information production technology is assumed to be identical for all analyst types and is given by $0.5c(\bullet)^2$. In reality, however, the sell-side analyst may face lower cost of information production due to factors such as industry specialization and better access to

\(^{11}\) That the broker’s cost function pertains to a single signal may seem to conflict with the assumption that buy-side analysts obtain a number of idiosyncratic signals from the sell-side analyst. However, this assumption is in the spirit of Kim and Verrecchia (1994) whereby a common source of information gives rise to multiple private idiosyncratic signals (e.g., multiple interpretations of the earnings number).
management. The model can be modified to incorporate such differences. However, the qualitative nature of the results presented below will remain the same.

Solving each of the two equations independently and taking into account that buy-side analysts are identical yields a system of two first-order conditions that correspond to (22) and (23), respectively:

\[
\frac{1}{2[2a + (M + 1)(d + e)]^2 \lambda} - cd = 0, \tag{24}
\]

and

\[
\frac{M}{4[2a + (M + 1)(d + e)]^2 \lambda} - ce = 0. \tag{25}
\]

Analysis of (24) and (25) yields the following proposition.

**Proposition 4**

Let \( \lambda_0, d_0 \) and \( 1/u_0 \) denote the equilibrium values of the market depth parameter, the precision of a buy-side analyst’s information, and the variance of liquidity trading in the endogenous benchmark setting, respectively. Then, equilibrium exists in this setting provided

\[
(\lambda / u - \lambda_0 / u_0) - 0.5c(Md^2 + e^2 - Md_0^2) \geq 0. \tag{26}
\]

In such equilibrium:

(i) The relation between \( d \) and \( e \) is given by \( e = 0.5Md \). Thus, when \( M \geq 3 \), the precision of the broker’s signal will exceed that of the buy-side analyst’s own signal. Furthermore,
total precision of private information, \(d+e\), is given by \((1+0.5M)d\), or alternatively, 
\[
\frac{M + 2}{M}e.
\]

(ii) The precision of a buy-side analyst’s own signal is decreasing in \(M\). The precision of the broker’s signal may either increase or decrease in \(M\). Therefore the relation between total precision of private information and \(M\) is ambiguous.

Condition (26) is intuitive: it states that the sum of all trading profits - net of aggregate information production costs - should be at least as high in the presence of the sell-side analyst as in his absence. If this is satisfied, then sell-side and buy-side will be able to share this (excess) profit and be better off relative to the benchmark setting. As discussed in Section 4 below, the condition \(\lambda/u - \lambda_0/\nu_0 \geq 0\) is satisfied when total precision of private information and/or the variance of liquidity trading in the presence of the sell-side analyst are sufficiently high. However, for equilibrium to exist it is also required that higher precision should be delivered at a cost that is not too high. The possibility that \(0.5c(Md^2 + e^2 - Md_0^2)\) can be negative indicates that, in fact, the presence of the sell-side analyst may work to reduce economy-wide expenditure on information production activities. This will be the case, for example, when total precision is the same with or without sell-side following (i.e., \(d+e = d_0\) implies \(Md^2 + e^2 - M(d+e)^2 < 0\)).

The source for such cost saving is economies of scale: the sell-side serves as an information source for multiple users thus substituting costly information gathering activity carried out individually by each one of those users.

As is implied by part (i) of the proposition in this equilibrium, provided there are more than two buy-side analysts, the bulk of information will be produced by the sell-side analyst.
The ratio of the precision of the broker’s signal to investors’ own signal will be increasing with the number of client-investors. That is, information production by the broker will crowd out buy-side analysts’ information gathering activities at a rate that is proportional to the number of informed investors.\(^{12}\) This also means that the buy-side analyst places greater weight on the sell-side analyst’s signal than on own signal.

As in the benchmark setting, buy-side analysts collect less information on their own the greater is the following of the stock among institutional investors (part (ii) of the proposition). Notably, the precision of the broker’s signal may \textit{increase} in \(M\). Therefore, whether total precision of the two signals also increases in \(M\) depends on the magnitude of adverse effect of \(M\) on \(d\).

Turning to the investigation of the properties of the market liquidity parameter, \(\lambda\), it should be pointed out that with endogenous information acquisition an increase in the number of buy-side analysts has two, possibly countervailing, effects on \(\lambda\). The direct effect, which is similar to that discussed in Proposition 3, works to increase \(\lambda\) as \(M\) increases. The second and \textit{indirect} effect is the one that relates to the effect of \(M\) on the total amount of private information produced in equilibrium.\(^{13}\) This second effect can be of either sign; however, it turns out that it is of second order of magnitude, implying that \(\lambda\) monotonically increases in \(M\). Finally, owing to the leakage effect, price informativeness is also positively related to \(M\). This is true notwithstanding the possibility that total precision of private information may decline in \(M\). This is because the latter effect on price efficiency is relatively small.

\(^{12}\) Note that this result is not driven by the assumption that the cost function is quadratic. A qualitatively similar result will be obtained for all marginal cost functions that are (quasi) convex.

\(^{13}\) Mathematically this effect is given by \(\frac{\partial \lambda}{\partial (d + e)} \times \frac{d(d + e)}{dM}\).
4. COMPARISON OF THE INFORMATION ENVIRONMENT BEFORE AND AFTER COVERAGE INITIATION BY THE SELL-SIDE ANALYST

In this section I explore how the initiation of firm coverage by a sell-side analyst affects the information environment. Using the analysis in the previous sections it is possible to address the following questions. First, does coverage initiation work to increase total amount of private information? Put this question differently, comparing firms with no sell-side analyst coverage to firms with sell-side following, which type of firm will be associated with more private information? The purpose of this line of inquiry is to inform research that is concerned with the incremental informational effects of public disclosures, such as earnings announcements (e.g., Dempsey, 1989, Lobo and Mahmoud, 1989, Shores, 1990). In this line of research, earnings are regarded as informative to the extent that they work to change the information set of market participants. Accordingly, earnings will have smaller effect the larger the amount of information possessed by informed investors in the pre-announcement period. Second, is the market more or less liquid in the presence of the sell-side analyst? This question has important empirical implications as higher market liquidity implies a more attractive market to potential investors because the share price is less sensitive to their demand. Higher liquidity works to reduce the required rate of return and increase price levels (Amihud and Mendelson, 1986, Brennan and Tamarowski, 2000). Also, believing that greater sell-side coverage and institutional holding work to increase liquidity, managers seem keen to increase sell-side analysts’ following (Trueman, 1996). Finally, I investigate whether price informativeness is positively affected by coverage initiation. This question is important because higher price efficiency implies better allocation of economic resources by investors across firms.
To answer these questions it is instructive to refer to the precision of the private signal produced by the buy-side analyst in the absence of the full-service broker. This is denoted by \( d_0 \). The next proposition summarizes the findings of this line of investigation.

**Proposition 5**

*Initiating coverage by the sell-side analyst when \( M > 1 \) results in*

(i) reduction in the precision of information produced by buy-side analysts unless the increase in variance of liquidity trading is sufficiently high;

(ii) higher total precision of private information;

(iii) higher market liquidity (i.e., lower \( \lambda \)), if the increase in variance of liquidity trading is sufficiently high;

(iv) lower price efficiency, unless \( (d+e) > 4ad_0/(M+1)d_0 - 2a \).

**Proof:** See the Appendix

The first result indicates that coverage initiation by the sell-side analyst that is not accompanied by greater liquidity trading generates an adverse effect on information production on the part of buy-side analysts. The intuition is that at the information production stage the buy-side analyst takes into account the availability of the sell-side analyst signal, which reduces the incentive to produce own signal. When coverage initiation involves greater demand by liquidity traders, there is a greater incentive to produce accurate information to take advantage of the uniformed. As a result, buy-side analysts may end up producing more information than without sell-side following. The second result is quite powerful and holds regardless of whether or not coverage
initiation involves greater liquidity trading. It points at a substitution effect: even in cases where buy-side analysts produce less precise information, the precision of the sell-side analyst signal is sufficiently high to compensate for the loss in the buy-side analyst’s accuracy. However, for this to be the case the number of institution-clients must be greater than one.

To understand the third finding (the effect on market liquidity), recall how the properties of $\lambda$ change across the two settings analyzed here. In the benchmark setting $\lambda$ is unimodal in the total precision of private information. Specifically, when private information is sufficiently precise $\lambda$ will be negatively related to the precision of private information. But in the presence of the sell-side analyst it will be positively and monotonically related to total precision due to the tax effect of trading commissions (see Proposition 3). These differences are clearly highlighted in Figure 1, where liquidity trading is kept constant across the two settings. As the graph illustrates, if the total precision is relatively low, the market may be more liquid (i.e., $\lambda$ may be lower) in the presence of the sell-side analyst, even if the total amount of information is higher.\(^\text{14}\) When total precision is relatively high, the market will be less liquid with sell-side following than without it. However, if sell-side coverage involves sufficiently higher demand on part of liquidity trading (i.e., sufficiently low $u$) the market will be more liquid. Pictorially, this would mean a parallel downshift of the dotted line below the solid one.

The intuition behind the fourth finding is that the tax effect on informed investors’ trading aggressiveness also works to reduce price informativeness. To illustrate this point note that assuming that total precision is the same across the two settings, price efficiency in the setting with the broker-analyst is lower than in the benchmark model. This is expected because when the precision is the same across the two settings, trading aggressiveness of investors is

\(^{14}\) Note that for equilibrium with a lower $\lambda$ to exist, the cost savings obtained by coverage initiation should outweigh
lower after coverage initiation by the sell-side analyst. Thus, for price efficiency to be higher in this setting, it is necessary for the total precision to also be higher than in the benchmark case. However, this is not a sufficient condition. Therefore, even if the total amount of private information is higher, but not sufficiently higher, price informativeness may be lower than before coverage initiation.

An issue which is of importance to regulators is the effect of coverage initiation on the profits of small individual investors. In this model, liquidity traders represent small individual investors. Liquidity traders generate loss that is equal to $\frac{\lambda}{u}$. Therefore, liquidity traders will sustain greater loss following coverage initiation whenever $\frac{\lambda}{u} > \frac{\lambda}{u_0}$. The following corollary states a condition under which this will be the case.

**Corollary 1**

A sufficient condition for $\frac{\lambda}{u} - \frac{\lambda}{u_0} > 0$ to hold is $\lambda(u_0) - \lambda(u) > 0$ and $u < u_0$. That is, the loss sustained by liquidity traders will be higher after coverage initiation if the demand of liquidity traders is the same before and after initiation and $\lambda$ is higher with sell-side following.

Due to the tax effect of trading commissions and higher total precision, $\lambda$ may be higher after coverage initiation by the sell-side analyst when demand of liquidity traders is unchanged. This implies that trading profits (i.e., gross profits excluding cost of private information) available to informed traders are higher as well. It is straightforward to show that $\frac{\lambda}{u}$ decreases in $u$. Since

the reduction in gross trading profits.
informed investors’ gain is liquidity traders’ loss, coverage initiation that involves \( u < u_0 \) will work to increase the loss sustained by liquidity traders.

5. EQUITY RESEARCH AND INVESTMENT BANKING

This section investigates how the information acquisition by sell- and buy-side analysts is affected by the presence of investment banking relationship at the full-service brokerage house (the sell-side analyst’s employer). It has been suggested in numerous places that sell-side analysts may bias their reports on stocks underwritten by the brokerage firm. Assuming that the market could undo such a bias, I focus here exclusively on the potential effect on the precision of private signals rather on the bias.\(^{15}\) The approach taken here captures the view that underwriting relationship increases the return on the sell-side analyst’s research activity. If the sell-side analyst’s research activities are restricted to solely attracting trading commissions with no other benefits (such those that emanate from investment banking relationships), this may lessen the willingness of the brokerage house to allocate costly resources to the research activity.

Specifically, and without loss of generality, I assume that investment banking relationship works to subsidize costly information acquisition by reducing the marginal cost of unit of signal precision.\(^{16}\) Let \( \delta, 0 < \delta \leq 1 \) denote the subsidy parameter whereby a smaller \( \delta \) corresponds to a higher level of subsidy. Assume further that the sell-side analyst’s cost function

\(^{15}\) This is consistent with common wisdom that institutions undo the bias on sell-side analysts’ recommendations. For example, Sernovitz (2002) reports that “Occasionally an analyst gives bankers and their clients the higher ratings they want – often with a tepidly positive rating like “outperform”. But in the candid conversations between analysts and institutional investors, the nuances of an investment are discussed. Official ratings almost never come up.” Similarly Kahn and Schwartz (2002) argue that “Perhaps the best result of the Spitzer probe will be if investors take a cue from institutions. They’ve long treated their research as just information rather than a reason to buy or sell a stock.”

\(^{16}\) The notion of such subsidy is also mentioned in Kahn and Schwartz (2002) who suggest that “Simply spinning off Wall Street research department won’t cut it. Only large institutional investors like mutual funds can afford to pay thousand of dollars for sophisticated independent research.” Private communications that I have had with sell- and buy-side analysts also confirm this view.
is now given by $0.5\delta ce^2$. This implies that the first order conditions for the optimal precision by the buy-side and sell-side analysts will be, respectively

$$\frac{1}{2[2a + (M + 1)(d + e)]^2} - cd = 0,$$

(27)

and

$$\frac{M}{4} \frac{1}{[2a + (M + 1)(d + e)]^2\lambda} - \delta ce = 0.$$

(28)

This immediately leads to the following corollary to Proposition 4.

**Corollary 2**

*In equilibrium with endogenous information acquisition and subsidy parameter $\delta$:*

1. Total precision of private information $(d+e)$ is increasing in the level of investment banking subsidy. That is, $(d+e)$ is decreasing in $\delta$.
2. The relation between $d$ and $e$ is given by $e = 0.5Md / \delta$. Thus, when $M>2\delta$, the precision of the broker’s signal will exceed that of the buy-side analyst’s own signal.

These results are intuitive: the sell-side analyst will tend to spend more resources on private information acquisition the greater the subsidy. This will result in his signal being more accurate. Buy-side analysts will correctly anticipate this; they will therefore cut back on own information acquisition activities. However, in the aggregate, total amount of information increases as overall costs decrease. This suggests that separating security research activities from investment banking activities within brokerage houses will lead institutional investors to
spend more on in-house research with the additional consequence that the total amount of private information being reduced.

Further implications include the possibility that investment banking subsidy works to reduce market liquidity but improve price efficiency. Moreover, with sufficiently large subsidy, coverage initiation by the sell-side analyst will lead to higher price informativeness than before coverage begun. Thus, reinforcement of the “Chinese Wall” within brokerage firms may have an unwarranted adverse effect on price efficiency.

6. EMPIRICAL IMPLICATIONS AND RELATION TO PRIOR THEORETICAL LITERATURE

In this section I discuss empirical implication of the model. For readers interested in understanding the contribution of this paper to other theoretical papers, I also provide a succinct literature review.

One of the main predictions of the model is that most of equity research will be carried out by sell-side analysts. This is consistent with the evidence provided in the 2000 Extel Survey of pan-European investment analysts. This survey reports that just 23% of fund managers who responded generated more than 50% of company results in-house. Similar finding is reported for in-depth research. That is, the majority of fund managers heavily rely on sell-side research.

The paper also relates to the literature in accounting and finance that utilizes sell-side analysts’ forecasts and recommendations as constructs for investors’ private information. An example of such use is the calculation of earnings surprises which incorporate sell-side analysts’ EPS forecasts (see, for a recent example, Kinney et. al, 2002). As another example, earnings forecasts may be used as a proxy for expected future (residual) earnings, or to estimate earnings
growth rates, in valuation models (e.g., Dechow et al., 1999). In these studies analysts’ forecasts are assumed to proxy for information available to investors in a pre-disclosure period, whereby the public disclosure itself may take place within few days, months or even years. Common to this literature is the omission of the possibility that sell-side analysts’ information constitutes only a subset of the overall information available to investors and that the various sources for private information may act as substitutes rather than compliments. Therefore, the use of sell-side analysts’ forecasts and recommendations as a metric for the overall amount of private information has been lacking theoretical support, which is provided here.\textsuperscript{17}

Coverage initiation by a sell-side analyst may result in a higher or lower market liquidity depending on its impact on total amount of private information available to investors and the increase in liquidity demand. To the best of my knowledge, there is no study that specifically compares market liquidity before and after coverage initiation. However, there are a handful of papers that attempt to link analyst following to market liquidity. Brennan and Subrahmanyam (1995) find that their proxy for Kyle’s $\lambda$ is inversely related to number of analysts following. Furthermore, Brennan and Tamarowski (2000) show that the greatest decline in Kyle’s $\lambda$ occurs for firms followed by one sell-side analyst. For example, stocks covered by one sell-side analyst exhibit $\lambda$ that is 49\% lower than stocks not followed by any sell-side analyst. The $\lambda$ for stocks covered by two sell-side analysts is 31\% lower than stocks covered by one sell-side analyst. This suggests that the greatest impact of analyst following on market liquidity occurs upon coverage initiation by the first sell-side analyst, the event studied in this paper. In the context of this paper’s model, higher market liquidity can follow coverage initiation if total information in the presence of the sell-side analyst is not too large relative to the benchmark case. In addition,

\textsuperscript{17} See Schipper (1991) for similar criticism of the use of analysts’ forecasts as a proxy for market expectations of
lower $\lambda$ can be explained if strong following by sell-side analysts also attracts greater trading by uninformed investors (i.e., noise traders), as is assumed here. Easley, O’Hara and Paperman (1998) investigate this latter possibility by analyzing a sample of NYSE stocks that differ in analyst coverage. Their results suggest that sell-side analysts may attract uninformed trading at a higher rate than informed trading. This, in turn, could explain the reduction in adverse selection costs observed by Brennan and Subrahmanyam.

Turning to the theoretical literature, the relation between public announcements and information selling activities has received very little attention in the accounting literature. Hayes (1998) examines the effect of bad vs. good news and restrictions on short-sales on an analyst’s incentive to gather information and produce optimistic reports. Like this paper, she considers commission revenues. Hayes finds that analysts’ forecasts will be more precise for stocks that performed well. She does not consider, however, the implications of the broker’s choice for price efficiency and market liquidity. In addition, Hayes’s results are based on the interaction between risk-aversion and client’s initial endowment of shares, a consideration that does not play a role here.

The result that the broker will benefit from informing as many clients as possible, while consistent with casual observation, stands in contrast to the findings of Admati and Pfleiderer (1988), Sabino (1993) and Fishman and Hagerty (1995). Admati and Pfleiderer argue that a risk-neutral analyst will never sell his information, as doing so will reduce the sum of his own trading profits and the fee he charges the client. Sabino and Fishman and Hagerty assume, like Admati and Pfleiderer, that an information seller (e.g., a sell-side analyst) can fully extract his clients’ trading profits. However, they show that an analyst can capture more of total trading profits by
disseminating his private information to a finite number of clients. Increasing the number of clients increases their incremental share in trading profits. At the same time, this also works to reduce total available trading profits owing to the increased competition among clients. The optimal number of clients is the one for which the two forces are just offsetting. This paper’s result is drastically different because the broker’s profits are linked to commission revenues and only indirectly to clients’ profits as agents cannot observe who the sell-side analyst informs. Furthermore, it is not assumed that the analyst has a monopolistic access to private information. Brennan and Chordia (1993) focus on optimal brokerage commission schedule when a risk-neutral information seller’s clients are risk-averse. They show that volume-based commission could be preferred to a fixed fee in paying for information. This paper, in contrast, takes the presence of commissions as a given institutional feature and does not attempt to explain their origin. Brennan and Chordia assume, unlike this paper, exogenous information. They also do not compare alternative channels for information gathering and, more important, do not investigate implications for pre-announcement information levels.

7. SUMMARY

Motivated by the debate on the role of sell-side analysts in the supply of private investment advice, this paper examines the effects of coverage initiation by a sell-side analyst on total amount of private information, market liquidity and price efficiency. The analysis focuses on the interaction between buy-side analysts and a sell-side analyst in information production activities, taking into account the existence of trading commissions as a mechanism for compensating sell-side analysts for collecting and disseminating private information.
One of the main findings of the paper is that coverage initiation by the sell-side analyst may work to reduce the amount of private information that buy-side analysts produce. In addition, the fraction of private information produced by the sell-side (buy-side) analyst increases (decreases) in the number of institutional clients. Notwithstanding this crowding-out effect, initiation of sell-side analyst coverage tends to increase the total amount of private information, especially if liquidity demand increases with sell-side following. In such a case, coverage initiation may lead to higher market liquidity and greater losses on part of liquidity traders (small individual investors).

It is shown that trading commissions paid for obtaining better information work to reduce trading aggressiveness. I call this latter phenomenon the tax effect of trading commissions. A consequence of this tax effect is that price efficiency may be lower in the presence of the sell-side analyst even if the amount of private information investors have is larger in the presence of the sell-side analyst.

The paper also looks at the likely effects of prohibiting equity research from being influenced by investment banking activity undertaken within the brokerage house. It is shown that in the absence of investment banking activity, sell-side analysts may collect information of lower quality. Imposing a “Chinese Wall” will shift the burden of information production to buy-side analysts with the overall consequence of lower amount of private information and less efficient security markets.
Figure 1

Comparison of the market liquidity parameter between the two settings

The red/dotted (black/solid) line depicts $\lambda$ for the market with (without) the sell-side analyst. The x-axis represents the weight $g$, which is equal to $(d+e)/(a+d+e)$ in the presence of the sell-side analyst and $d_0/(a+d_0)$ in the benchmark setting. In this example $M=10$, $a=u=u_0=1$. Note that the intersection of the two lines occurs when total precision is 0.125. For values higher than 0.125, $\lambda$ will be higher (and gross profits of informed investors will also be higher) in the setting with the sell-side analyst.
Appendix

Proof of Lemma 1

At the trading stage, each investor maximizes his expected profits function:

\[
\max_i E(\pi_i \mid z_i) = E[(v - P(x_i))x_i \mid z_i] = \left[g_i z_i - \lambda[(M - 1)\alpha_j g_i z_i + x_i]\right]x_i ,
\]

where \(\alpha_j\) denotes the \(i\)th investor conjecture of the \(j\)th investor’s trading strategy. Differentiation with respect to \(x_i\), and assuming \(x_i = \alpha_i z_i\) and \(x_j = \alpha_j z_j\), yields the first-order-condition

\[
\alpha_i = g_i[1 - \lambda(M - 1)\alpha_j]/2\lambda .
\]

(A.2)

Requiring that \(\alpha_i = \alpha_j = \alpha\) and \(g_i = g_j = g\) (i.e., all investors are identical) implies:

\[
\alpha = \frac{g}{\lambda[2 + (M - 1)g]} .
\]

(A.3)

Now, the market depth parameter is defined as

\[
\lambda = \frac{\text{cov}(v, w)}{\text{var}(w)} = \frac{M\alpha\gamma_u}{M\alpha^2 \gamma_{uv} + M(M - 1)\alpha^2 \gamma_u + \gamma_w} .
\]

(A.4)

Solving (A.3) and (A.4) simultaneously yields Equations (6) and (7) in the text.

Proof of Proposition 2

This proof begins by first deriving comparative statics for the optimal precision. Using this, it then continues to prove the three parts of the Proposition.

Optimal precision

The \(i\)th investor’s profit, as a function of the optimal demand \(x_i = \alpha_i z_i\) and the conjecture \(\alpha_j\), is given by

\[
[g_i z_i - \lambda[(M - 1)\alpha_j g_i z_i + \alpha_i z_i]]\alpha_i z_i - 0.5cd_i^2
\]

\[
\Leftrightarrow
\]

\[
z_i^2[g_i\alpha_i[1 - \lambda(M - 1)\alpha_j] - \lambda\alpha_i^2] - 0.5cd_i^2 .
\]

(A.5)
Now, from the first-order-condition (A.2) we know that
\[ \alpha_i = g_i [1 - \lambda(M - 1)\alpha_j]/2\lambda. \]

Therefore, (A.5) can be rewritten as
\[ \frac{(g_i z_j)^2 [1 - \lambda(M - 1)\alpha_j]^2}{4\lambda} - 0.5cd_i^2. \]  
(A.6)

Using the fact that
\[ E(g_i z_j)^2 = \frac{g_i}{a}, \]
the expectations of (A.6) is given by
\[ \frac{g_i [1 - \lambda(M - 1)\alpha_j]^2}{a} \frac{1}{4\lambda} - 0.5cd_i^2. \]  
(A.7)

Differentiating (A.7) with respect to \( d_i \):
\[ \frac{1}{(a + d)^2} \frac{[1 - \lambda(M - 1)\alpha_j]^2}{4\lambda} - cd_i = 0. \]  
(A.8)

It is simple to show that the sign of the derivative of (A.8) with respect to \( d_i \) is negative, implying that \( d_i \) is a solution to a maximization problem. Using the fact that in equilibrium \( d_i = d_j = d \) and that
\[ [1 - \lambda(M - 1)\alpha] = \frac{2}{[2 + (M - 1)g]} \]
it is possible to rewrite (A.8) as an equilibrium condition:
\[ \Gamma \equiv \frac{1}{\sqrt{M(d(a + d)\eta[2a + (M + 1)d]} - c = 0. \]  
(A.9)

Employing the implicit function theorem it is straightforward to show that
\[ \frac{d\Gamma / dc}{\partial c} < 0, \]
since $\partial \Gamma / \partial c = -1$ and $\partial \Gamma / \partial d = -\frac{6a^2 + 6d^2(M + 1) + ad(13 + 5M)}{2d^2(a + d)(2a + d(M + 1))^2 \sqrt{\frac{d(a+d)mu}{a}}} < 0$.

In addition

$$\frac{dd}{dM} = -\frac{\partial \Gamma / \partial M}{\partial \Gamma / \partial d} < 0$$

since $\partial \Gamma / \partial M = -\frac{2a + d(1 + 3M)}{2dM(2a + d(M + 1))^2 \sqrt{\frac{d(a+d)mu}{a}}} < 0$.

I now turn to prove the three parts of Proposition 2.

Part 1

Note that

$$\frac{d\lambda}{dc} = \frac{d\lambda}{dd} \cdot \frac{dd}{dc}.$$ 

From Proposition 1 we know that the depth parameter is unimodal with a maximum in $d$. Since $d$ is inversely related to $c$, it follows that with endogenous information acquisition activities the depth parameter is also unimodal with a maximum in $c$.

Part 2

$$\frac{d\lambda}{dM} = \frac{\partial \lambda}{\partial M} + \frac{\partial \lambda}{\partial d} \cdot \frac{dd}{dM}.$$ 

Note from Proposition 1 that each part of the derivative can be of either, and potentially of opposing, sign. Thus, the overall sign of this expression is ambiguous.

Part 3

Recall from Eq. (8), the calculation of which is provided on p. 45, that

$$I = \frac{1}{a} \left[ \frac{2a + d}{2a + (M + 1)d} \right].$$

It is straightforward to show that $dl/dd < 0$. Since $d$ is negatively related to $c$ it follows that $dl/dc > 0$. Now,
\[
\frac{dI}{dM} = \frac{\partial I}{\partial M} + \frac{\partial I}{\partial d} \cdot \frac{dd}{dM} = \frac{\partial I}{\partial M} - \frac{\partial I}{\partial \Gamma} / \partial d = \frac{d(a + 2d)(4a + 3d)}{a(2a + d(M + 1))(6a^2 + 13ad + 5adM + 6d^2(M + 1))} < 0.
\]

**Calculation of Equations (13) and (14)**

At the trading stage, each investor maximizes his expected profits function

\[
\max_{x_i} E(\pi_i | z_i) = E[(v - P(x_i))x_i | z_i, s_i] - t(qx_i)^2
\]

(A.10)

\[
= \left\{ \frac{dz_i + es_i}{a + d + e} - \lambda[(M - 1)(\beta_j + \gamma_j)] \frac{dz_i + es_i}{a + d + e} + x_i \right\} x_i - t(qx_i)^2,
\]

where \(\beta_j\) and \(\gamma_j\) denote the \(i\)th investor’s conjecture of the parameters of the \(j\)th investor’s trading strategy. Differentiating (A.10) with respect to \(x_i\) yields the first-order-condition as follows:

\[
\frac{dz_i + es_i}{a + d + e} [1 - \lambda(M - 1)(\beta_j + \gamma_j)] = 2[\lambda + tq^2]x_i.
\]

(A.11)

Recall that \(x_i\) is conjectured to take the form \(x_i = \beta_i z_i + \gamma_i s_i\). Thus, (A.11) can be transformed into a system of two equations with two unknowns \(\beta_i\) and \(\gamma_i\):

\[
h[1 - \lambda(M - 1)\gamma_j] = [\lambda(2 + (M - 1)h) + 2tq^2]\beta_i
\]

(A.12)

and

\[
k[1 - \lambda(M - 1)\beta_j] = [\lambda(2 + (M - 1)k) + 2tq^2]\gamma_i.
\]

(A.13)

Solving this system while requiring \(\beta_i = \beta_j = \beta\) and \(\gamma_i = \gamma_j = \gamma\) results in Equations (13) and (14) in the text.

**Proof of Lemma 2**

From Equation (16) in the text we know that

\[
t = \frac{\lambda[2 + (M - 1)(h + k)]}{2q^2}.
\]
Substituting this into (13) and (14) and simplifying we get:

\[ \beta = \frac{h}{2\lambda[2 + (M - 1)(h + k)]}, \quad (A.14) \]

and

\[ \gamma = \frac{k}{2\lambda[2 + (M - 1)(h + k)]}. \quad (A.15) \]

Now

\[
\lambda = \frac{M\text{cov}(\beta z_i + \gamma s_i, v)}{\text{var}(\sum x_i + x_u)} = \frac{M\text{cov}(\beta z_i + \gamma s_i, v)}{M\text{var}(x_i) + M(M - 1)\text{cov}(x_i, x_j) + \frac{1}{u}}.
\]

(A.16)

It is straightforward to show that the numerator of the right-hand-side of (A.16) is equal to

\[
\frac{M(h + k)/a}{2\lambda[2 + (M - 1)(h + k)]},
\]

and that the denominator of the right-hand-side of (A.16) is equal to

\[
\frac{1}{a} \left[ \frac{M(h + k) + M(M - 1)(h + k)^2}{4\lambda^2[2 + (M - 1)(h + k)]^2} \right] + \frac{1}{u}.
\]

Using these expressions, further manipulation of (A.16) generates

\[
M(h + k)[1 + (M - 1)(h + k)] + 4\lambda^2[2 + (M - 1)(h + k)]^2 \frac{a}{u} = 2M(h + k)[2 + (M - 1)(h + k)].
\]

This results in Equation (19) in the text:

\[
\lambda = \sqrt{\frac{M(h + k)[3 + (M - 1)(h + k)]\frac{a}{u}}{2[2 + (M - 1)(h + k)]}}.
\]

Using the solution for \( \lambda \) in (A.14) and (A.15) yields equations (17) and (18).
Calculation of the conditional variance

First note that, generally, the variance of \( v \) conditional on the order flow, \( w \), is given by

\[
\text{var}(v \mid w) = \text{var}(v) - \frac{\text{cov}^2(v, w)}{\text{var}(w)}
\]

A. Benchmark setting

In this setting the conditional variance is

\[
\text{var}(v \mid w) = \frac{1}{a} - \frac{(M \alpha \gamma_2)}{M \alpha^2 \gamma_2 + M(M-1)\alpha^2 \gamma_2 + \gamma_2}
\]

Recall that

\[
\alpha = \sqrt{\frac{g a}{M u}},
\]

implying that (A.13) can be written as

\[
\text{var}(v \mid w) = \frac{1}{a} - \frac{M g \gamma_2}{2 + (M-1)g}.
\]

Using the definition of \( g \), straightforward simplification yields Eq. (8) in the text.

B. Setting with a sell-side analyst

In calculating the conditional variance for this setting, note that

\[
\text{var}(w) = \frac{4 + 2(M-1)(h+k)}{3 + (M-1)(h+k)} \frac{1}{u}
\]

and,

\[
\text{cov}^2(v, w) = \frac{M(h+k)/a}{3 + (M-1)(h+k)} \frac{1}{u}.
\]
This implies that

\[
\text{var}(v \mid w) = \text{var}(v) - [\text{cov}^2(v, w) / \text{var}(w)] = \frac{1}{a} \left[ 1 - \frac{M(h + k)}{4 + 2(M - 1)(h + k)} \right]
\]  
(A.18)

Using the definitions of \(h\) and \(k\), straightforward simplification yields Eq. (21) in the text.

**Calculation of Equations (24) and (25)**

The \(i\)th investor’s expected profits, as a function of the optimal demand \(x_i = \beta_i z_i + \gamma_i s_i\) and the conjectures \(\beta_j\) and \(\gamma_j\), is given by (ignoring the fix term \(F\))

\[
[h_i z_i + k_i s_i] - \lambda [(M - 1)(\beta_j + \gamma_j)(h_i z_i + k_i s_i) + (\beta_i z_i + \gamma_i s_i)](\beta_i z_i + \gamma_i s_i) - t q^2 (\beta_i z_i + \gamma_i s_i)^2 - 0.5 c d_i^2
\]

\[
\Leftrightarrow
(h_i z_i + k_i s_i)[1 - \lambda (M - 1)(\beta_j + \gamma_j)](\beta_i z_i + \gamma_i s_i) - (\lambda + t q^2)(\beta_i z_i + \gamma_i s_i)^2 - 0.5 c d_i^2. \quad (A.19)
\]

Now, from the first-order-condition (A.13) we know that the \(i\)th investor’s optimal demand is a function of his conjecture of other investors’ demand as follows:

\[x_i = \beta_i z_i + \gamma_i s_i = \frac{(h_i z_i + k_i s_i)[1 - \lambda (M - 1)(\beta_j + \gamma_j)]}{2(\lambda + t q^2)}.
\]

Therefore, (A.16) can be written as

\[
\frac{(h_i z_i + k_i s_i)^2[1 - \lambda (M - 1)(\beta_j + \gamma_j)]^2}{4(\lambda + t q^2)} - 0.5 c d_i^2. \quad (A.20)
\]

Using the fact that

\[
E(h_i z_i + k_i s_i)^2 = \frac{h_i + k_i}{a},
\]

the expectations of (A.20) is given by

46
\[
\frac{h_i + k_i}{a} \left[ 1 - \frac{\lambda}{4(\lambda + tq^2)} \right]^2 - 0.5cd_i^2. \tag{A.21}
\]

Now, since \( t = \frac{\lambda[2 + (M-1)(h_i + k_i)]}{2q^2} \), (A.21) can be further simplified to obtain
\[
\frac{h_i + k_i}{a} \left[ 1 - \frac{\lambda}{2\lambda[4 + (M-1)(h_i + k_i)]} \right] - 0.5cd_i^2. \tag{A.22}
\]

Differentiating (A.19) with respect to \( d_i \), setting the resulting expression to zero and using the fact that in equilibrium \( d_i = d_j = d \), and

\[
[1 - \frac{\lambda}{2 + (M-1)(h + k)}] = \frac{4 + (M-1)(h + k)}{2[2 + (M-1)(h + k)]}
\]

yields Eq. (24) in the text:

\[
\frac{1}{2[2a + (M+1)(d + e)]^2} - cd = 0
\]

It is simple to show that the sign of the derivative of (24) with respect to \( d_i \) is negative, implying that \( d_i \) is a solution to a maximization problem.

Now, the broker’s maximization problem is given by

\[
\max_{\pi_b} \pi_b = E(R) - 0.5ce^2 = M \frac{h + k}{8a} \frac{1}{\lambda[2 + (M-1)(h + k)]} - MF - 0.5ce^2. \tag{A.23}
\]

Straightforward differentiation of (A.23) yields Eq. (25) in the text.

**Proof of Proposition 5**

**Part 1**

In the absence of the sell-side analyst \( d_0 \) will satisfy (A.16)
After coverage initiation $d$ should satisfy

$$\frac{1}{\sqrt{Md_0(a+d_0)^{\frac{w}{v}}[2a+(M+1)d_0]d_0}} - c = 0.$$  

Inspecting these expression reveals that they both decrease in the precision of the signal produced by the buy-side analyst. Comparing these two expressions note that for $d=d_0$ and $u=u_0$ we get

$$\frac{1}{\sqrt{M(d+e)(3a+(M+2)(d+e))^{\frac{w}{v}}[2a+(M+1)(d+e)](d+e)}} - c < 0.$$  

Therefore, in equilibrium $d$ must be lower than $d_0$ when $u=u_0$. However, since $d$ is positively related to $1/u$, a sufficiently high $1/u$ will result in $d>d_0$.

Part 2

Let $n=d+e$ and $\lambda$ denote total precision and the market depth parameter, respectively, in the setting with the sell-side analyst and let $d_0$ and $\lambda_0$ denote total precision and the market depth parameter, respectively, in the benchmark setting. Then, in the setting with the sell-side analyst $n$ must satisfy

$$\frac{1}{[2a+(M+1)n]} \cdot \frac{1}{\sqrt{M\lambda}} \cdot \frac{M+2}{2\sqrt{3a+(M+2)n}} = cn.$$  

(This is obtained by combining Eq. (24) and (25) into one equation and using Eq. (20) to substitute for $\lambda$.) The equivalent condition in the benchmark setting is

$$\frac{1}{[2a+(M+1)d_0]} \cdot \frac{1}{\sqrt{Md_0}} \cdot \frac{1}{\sqrt{a+d_0}} = cd_0.$$  

Note that for $M>1$, $u=u_0$, and $n=d_0$ we have
\[
\frac{1}{[2a+(M+1)d_0]} \cdot \frac{1}{\sqrt{Md_0 \frac{u}{\pi}}} \cdot \frac{M+2}{2\sqrt{3a+(M+2)d_0}} > cd_0.
\]

Thus, total precision in the setting with the sell-side analyst, \( n \), must be larger than \( d_0 \) for \( M>1 \) and \( u=u_0 \). Since \( d \) is positively related to \( 1/u \), \( n \) will exceed \( d_0 \) when \( u<u_0 \).

**Part 3**

The relation between \( \lambda \) and \( \lambda_0 \) can be expressed as the following ratio

\[
\frac{\lambda}{\lambda_0} = \sqrt{\frac{n[3a+(M+2)n]u}{4d_0[a+d_0]u_0}}
\]

It is straightforward to show that \( \frac{d\lambda}{du} = \frac{\partial\lambda}{\partial u} + \frac{\partial\lambda}{\partial n} \frac{dn}{du} > 0 \). Therefore, if \( \lambda/\lambda_0 \geq 1 \) for \( u=u_0 \), there must be a value \( u^* \) such that \( u^* < u_0 \) and \( \lambda(u^*)/\lambda_0 < 1 \). Clearly, if \( \lambda/\lambda_0 < 1 \) for \( u=u_0 \), \( \lambda/\lambda_0 \) will be smaller than one for all \( u<u_0 \).

**Part 4**

Let \( I \) (\( I_0 \)) represent price efficiency in the setting with (without) the sell-side analyst. Then

\[
a[I-I_0] = \frac{4a+(M+2)n}{4a+2(M+1)n} - \frac{2a+d_0}{2a+(M+1)d_0}.
\]

Now, price efficiency will be higher in the setting with the sell-side analyst when \( I-I_0<0 \). This condition can be restated as

\[
4ad_0 + n[(M+1)d_0 - 2a] < 0
\]

or, alternatively

\[
n > \frac{4ad_0}{(M+1)d_0 - 2a}.
\]
REFERENCES


