The Dynamic Competitive Effect of Reputation Acquisition: Evidence from the Financial Analyst Market

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Abstract

This paper studies the dynamic reputation game between sell-side analysts. It finds that less-reputable analysts are more likely to make bold earnings forecasts in an attempt to acquire reputation. As a result, a more competitive environment may induce the analysts to distort their forecasts because of stronger reputation acquisition motive. It estimates a dynamic model where analysts' strategy with respect to their own reputation changes over time and across markets due to different behavior of the actual earnings. It develops an methodology to use the observable actual earnings to control for the non-stationarity in analysts' strategy.

1 Introduction

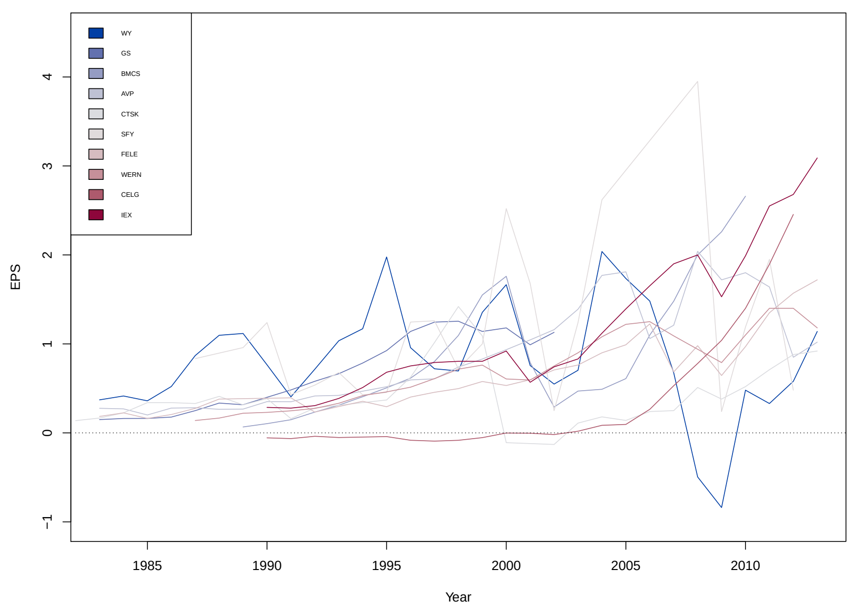
Reputation often disciplines players' behavior in a market. For example, a newspaper could lose readership if its readers found out that it provided false information. A seller on Amazon would lose sales if its product is loaded with bad reviews. Therefore, a newspaper or a seller that hopes to stay in the market provides quality product to their consumers to acquire reputation.

The same story applies to analysts in the financial industry. In the sell-side market, analysts conduct research on the securities they choose to cover and make forecasts about the future performances of the securities. Their forecasts are made public eventually. Once the true security performance is revealed, investors and brokerage firms can observe analysts' forecast accuracy. Analysts with good reputation of forecast accuracy are hired by much better-paid brokerage firms. The firms are also motivated by reputation among the investors to seek accuracy in their employees' analysis. Incentivized by higher wages, sell-side analysts desire to become more reputable, hence are disciplined to make accurate forecasts.

However, reputation acquisition might also induce bold behavior in a competitive environment. If reputation is based on how well an analyst performs relative to the others, it will change analysts' forecast behavior. They may strategically exaggerate their forecast or make forecasts that contradict the other analysts' forecast so that their reputation could increase dramatically if they turn out to be right. However, if there is only one analyst in the market, the incentive to outperform will be replaced by the disciplining effect of reputation. Therefore, through the channel of reputation acquisition, competition may induce more distortion, even in an environment where absolute accuracy is valued. This paper empirically investigates this channel in the dynamic competition between sell-side analysts. I will focus on earnings per share forecast in the US securities market, following the literature.

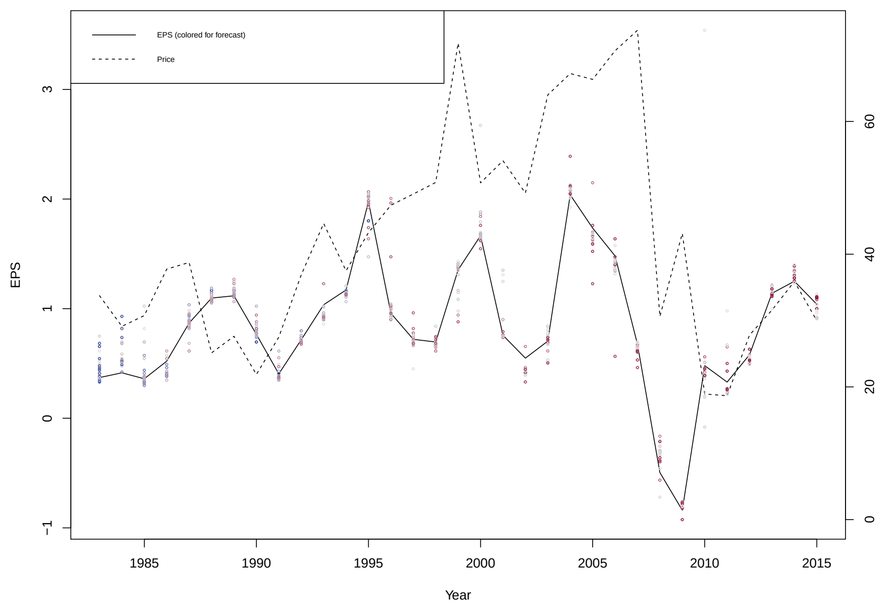
A major challenge of this study is that boldness is context-specific. A forecast that deviates tremendously from a security's earnings last period could be considered bold for a security that behaves steadily overtime, but normal for a security that fluctuates constantly. This is the *security* context. Moreover, a forecast that is lower than a security's earnings last period should be considered bold if the market has been booming, but again normal if the market has been in a crash. This is the *time* context. Figure 1 illustrates earnings fluctuations over the last 30 years for 10 randomly selected securities. It shows that there is indeed a lot of variations in the earnings behavior over time and across securities. It is a dynamic competition where the players are constantly changing strategies in response to the environment. The analysts' strategies might be non-stationary over time and across securities.

Figure 1: Examples of Earnings Fluctuations



This paper proposes a novel methodology to analyze the dynamic competition in non-stationary environment making use of the wealth of data in the financial market. The key idea is that even though analysts' strategy is non-stationary overtime, the non-stationarity is generated by the changes in the actual earnings per share, which is observable. Figure 2 displays the analysts'

Figure 2: Example of the Relationship between Forecasts and Earnings



forecasts together with the actual earnings fluctuation. The forecasts closely follow the actual earnings. Therefore, the non-stationarity in forecast strategy at the analyst level can be controlled with the earnings time series.

To implement this idea, I build and estimate a structural model of analysts' dynamic reputation game. The model takes analysts' reputation as a state variable and analysts' decision to make forecasts and forecast values as actions. In order to control for the non-stationarity, I also include securities' actual earnings as a state variable.

I extend the two-stage algorithm of Bajari et al. (2007) (BBL) to estimate the model. In the first stage of BBL's algorithm, the transition probability of state variables and the policy function are estimated. In the second stage, the estimated transition probability and the policy function are used to simulate the value function. I extend the first stage by including an *aggregate state variable*, that is the actual earnings. The main characteristic of this state variable is that its transition probability does not depend on the transition probability of other state variables in the dynamic competition or players' actions. I can estimate the transition probability and the policy function conditioning on the aggregate state variable and estimate the stochastic process of this variable separately. This methodology contributes to the literature on the estimation of dynamic games (e.g., Hotz and Miller (1993), Hotz et al. (1994), Rust (1987)).

In the first stage of the BBL estimation, which also serves as the reduced-form evidence, I first find that analysts' probability of receiving high-reputation depends on their forecast performance. Moreover, low-reputation analysts exhibit more strategic forecasting behavior than high-reputation analysts: their forecast errors respond increase with competition, compared to high-reputation analysts.

Building on this, I estimate security analysts' payoffs with low and high reputation. I find that y analysts are mostly driven by long-term reputation acquisition incentive rather than short-term bonus earning incentive. High-reputation analysts receive a much higher fixed wage than low-reputation analysts. Meanwhile, analysts' forecast performance have an insignificant effect on their immediate bonus compensation. Low-reputation analysts can acquire reputation and consequently higher future wage by outperforming their rival. This results in stronger strategic incentive for low-reputation analysts, consistent with the reduced-form evidence.

This paper contributes to the literature on competition and bias in the financial market. Hong and Kacperczyk (2010) find that less competition between sell-side analysts increases optimism bias. A simple regression of average forecast bias for a security on the number of analysts suffers from endogeneity from selection. Analyst may choose to make forecasts on securities which are expected to have optimistic behavior. They overcome this problem using a natural experiment. When there are mergers and acquisitions between brokerage firms, all but one of the analysts with overlapping coverage are fired. This reduces the level of competition in the market. They also find that the increase in bias most likely comes from the independence rationale channel of Gentzkow and Shapiro (2006), that is, an analyst is less likely to be caught distorting her forecast. This paper investigates a different channel, namely the reputation accumulation channel. Also, it allows counterfactual analysis of how analysts may behave in a less competitive environment.

Clarke and Subramanian (2006) also study the relationship between analysts' reputation and the boldness of their forecasts. They find that analysts with the worse and the best reputation are more likely to make a bold forecast. The less-reputable analysts make bold forecasts in an attempt to build reputation, whereas for the most reputable analysts, mistakes are less costly. Their paper is based on a learning model in which analysts themselves and the investors learn about analysts' ability, and it does not cover the competitive effect of reputation.

As mentioned in Bradshaw (2011), structural analysis in this literature is rare. A recent attempt has been made by Camara (2015). She studies how preemption affects forecast delays and forecast accuracy using timing data on earnings forecasts. Her paper estimates a timing game between the analysts but this paper focuses on a reputation game.

The rest of the paper is organized as follows. Section 2 introduces the sell-side research industry. Section 3 presents the data and the summary statistics. Section 4 sets up the model and characterizes the equilibrium. Section 5 and 6 explains the estimation procedure and reports the results. Section 7 concludes and discusses paths for future research.

2 Industry Background: Sell-Side Research

Sell-side analysts conduct research on securities and make forecasts about their performances. The results are presented to retail and institutional investors in investment reports, as well as in paperless forms such as meetings with subject companies' management teams. Traditionally, both investors and subject companies rely on sell-side analysts to facilitate the flow of information[1]. Through sell-side analysts, investors learn about subject companies' business models, projected future earnings and stock prices to make investment decisions, while subject companies attract funds.

Forecast Inputs to the earnings forecast include past financial information on the subject company, evaluation of the competitive environment, communication with the company's management team and the potential investors and so on.

Forecast period varies from a quarter to over five years, the most common being a quarter and a year. The forecast process is fairly flexible. Take annual forecast as an example. Analysts can start to release forecasts about a company's year-end financial figures at the beginning of the fiscal year. They can continue to review or release new forecasts for the same fiscal year until the true earnings figures are revealed one to two months after the fiscal year end. Eventually, all forecasts are disclosed to the public, however, analysts and brokerage firms are allowed to disclose their forecasts early to a few clients before public disclosure.

Brokerage firms The biggest employers of sell-side analysts are brokerage firms[2], whose core business is the creation and sales of financial instruments, e.g., underwriting service. Sell-side analysts are typically hired to provide information on these instruments. Their payoff used to be heavily associated with sales of the instruments they covered. As a result, analysts were incentivized to guide investors to buy instruments that generate more commission or underwriting spread for brokerage firms. In 2003, an enforcement agreement, the Global Analyst Research Settlement (the Settlement), was reached between the United States Securities and Exchange Commission (SEC), Financial Industry Regulatory Authority (FINRA), New York Stock Exchange (NYSE), and ten of the United States' largest brokerage firms. This settlement mandates that these firms block their research department from investment banking department both physically and with a Chinese Wall. After the settlement, the agency problem due to the link between sales and research significantly weakened. Today, sell-side analysts also provide fee-based research and subscription-based research services. The former is compensated by the subject company hoping to disclose information more

[1] The flow of information remains dependent on sell-side analyst today, however, the rising artificial intelligence is quickly replacing the sell-side analysts in recent two years due to its lower cost. It will be interesting to see how this affects the competition and henceforth the efficiency of the market but for this version of the paper, it is out of the scope.

[2] Besides being hired by traditional brokerage firms, sell-side analysts may also be hired by research firms or self-employed. Because brokerage firms encompass the services provided by these other firms, I refer to all of them as brokerage firms hereafter for simplicity.

efficiently to investors. The latter is compensated by report readers on a subscription or pay-per-view basis. An agency problem might still arise in these scenarios, but because the Settlement also informed the investors, brokerage firms constantly providing overly-favorable information would have trouble creating a market on the buy-side, ultimately hurting their sell-side business. In other words, reputation concern regulates the firms' incentives so that they value accuracy in sell-side research.

Reputation and payoff Analysts' reputation is implied by the sizes of their employing brokerage firms, because there is a clear hierarchy in the sell-side research industry both in terms of reputation and salary. An analyst job at a big brokerage firm, or as the industry calls it, a *wirehouse*, such as Wells Fargo and Morgan Stanley, is nearly always more reputable and better-paid than an analyst job at a regional firm such as Raymond James and Stifel. The latter subsequently dominates jobs at other smaller firms. The hierarchy and the perfect alignment of reputation and salary are due to the network effect in the brokerage industry. Institutional investors are the biggest players on the buy-side. They interact with more brokerage firms and have better information to judge the quality of sell-side research. In fact, an annual survey is conducted by the magazine *Institutional Investor* among buy-side money managers to calculate a ranking of sell-side analysts. The names of the top analysts are publicly available and the rest available through the magazine. The ranking is often cited as a benchmark for analysts' reputation. In other words, sell-side analysts' reputation is determined by institutional investors. Due to large investment volume, institutional investors are typically served by wirehouses, whose preference for analysts consequently aligns with them. With better buy-side connection, wirehouses also attract more profitable firms on the sell-side, which contribute to better monetary payoff for analysts. Hence, sell-side analysts' reputation, which positively correlates with their salaries, can be inferred from the size of their employers.

Competition Due to the hierarchy, sell-side analysts compete to be employed by the biggest brokerage firms. Employment in this market is highly mobile. An analyst is typically employed by multiple brokerage firms throughout his/her career. Because forecasts are eventually publicly available and there are parties such as the *Institutional Investor* magazine that rank the analysts by their current-period performance, an analyst that performs better than its peers can be quickly promoted to more reputable brokerage firms.

3 Data

This paper uses data on annual forecasts of Earnings Per Share (EPS) of publicly listed US companies from the Institutional Brokers' Estimate System (IBES) detail history dataset announced between January 1st 1982 and September 30th 2015. For each EPS forecast, the data contains the forecast value, the corresponding actual EPS and identifying information of the security, the forecasting analyst, and the brokerage house. I match the securities in the IBES dataset to the Center for Research in Security Prices (CRSP) database for daily stock prices, stock returns, and the number of outstanding shares. The securities are also matched to the Compustat database for an alternative measure of actual earnings per share and other financial information for robustness checks.

I define the sample to be securities that are present in all three datasets for more than 20 years during the observed period. Each security is considered as a separate market on which multiple analysts release earnings forecasts. Because we are interested in the competitive effect of reputation accumulation, a security needs to be observed over a long period of time for reputation accumulation to be feasible. For estimation, I further restrict to a subsample of 698 securities without potential outlier observations or coding errors, following Hong and Kacperczyk (2010).[3] Table 1 presents the summary statistics of the full sample by forecast, security, and analyst.

Reputation Measures To proxy analysts' reputation in the sell-side research market, I construct the following measures. *Rank* represents the reputation of the analyst that makes a forecast. It is defined as the rank in size of the brokerage firm that employs the forecasting analyst. If an analyst has multiple employers in a given year, the maximum *Rank* is taken as the analyst's *Rank*. If an analyst no longer makes forecast on a given security, I will assign a rank of zero. The rank in size of the brokerage firm is defined as the yearly rank percentile in brokerage firm size. Following Camara (2015), I measure brokerage firm size by the number of analysts it employs.[4] Formally, for brokerage firm h in time t,

$$Rank_{ht} = Quantile(\#\text{Employed Analysts in Brokerage Firm h in Time t}).$$

This measure assumes that a firm has the same rank across all industries it covers and captures the overall rank of the brokerage house. To capture the industry specialization of brokerage houses, I refine the measure to introduce variation at the industry level. For industry d,

$$Rank^d_{ht} = Quantile(\#\text{Employed Analysts in Brokerage Firm h in Industry d, Time t}).$$

I classify an analyst as having high reputation in an industry if the $Rank^d_{ht}$ of the analysts' employing brokerage house is above 0.9 , i.e., it is one of the top 10% largest brokerage houses in the industry and low reputation otherwise. If an analyst leaves the sell-side industry, I classify the analyst as terminated.

[3] I remove the securities whose forecast errors are greater than 10 dollars because they may be subject to coding errors. I also remove securities whose average optimism bias across analysts is ever more than the 99.5th percentile of all security-years, as they may be outliers.

[4] Alternative measures include the number of securities a brokerage firm covers and the market capitalization of the securities a brokerage firm covers. Because only a numeric identifier is observable for each brokerage firm, we cannot link it to firm-level information that is not contained in the dataset.

Table 1: Summary Statistics

Statistic	Mean	S.D.	Min	Median	Pctl(75)	Max
A. Forecast (276,359 Obs)						
Fiscal Year			1,982	2,000	2,008	2,016
Rank	0.848	0.172	0.051	0.916	0.970	1.000
EPS(USD)	1.210	1.113	−2.590	0.960	1.800	4.680
EPS-Compustat (USD)	1.759	2.464	−76.520	1.670	2.710	157.450
EPS Forecast(USD)	1.222	1.126	−17.320	0.975	1.800	119.608
Forecast Error	0.094	0.325	0.000	0.030	0.080	115.568
Optimism	0.012	0.338	−18.950	−0.003	0.020	115.568
B. Security-Year (817 Securities. 21,731 Obs.)						
#Analysts	12.711	10.152	1	10	18	69
Total #Analysts	90.546	60.109	8	73	128	341
#Brokerages	11.735	9.219	1	9	17	60
Total #Brokerages	55.409	31.639	2	48	77	195
EPS(USD)	1.042	1.057	−2.590	0.810	1.580	4.680
Years in Sample	27.292	4.334	21	27	32	34
Mean Forecast Error	0.101	0.438	0.000	0.042	0.101	57.984
S.D. Forecast Error	0.079	0.583	0.000	0.032	0.080	81.436
Mean Optimism	0.018	0.441	−3.286	−0.002	0.029	57.584
S.D. Optimism	0.087	0.577	0.000	0.035	0.090	82.002
C. Analyst-Year (13,543 Analysts. 84,590 Obs.)						
Tenure	6.451	5.495	1	5	9	34
#Past Employers	2.814	2.116	1	2	4	18
Overall Rank of Current Employer	0.839	0.174	0.051	0.904	0.968	1.000
Mean Forecast Error	0.160	0.467	0.000	0.087	0.179	107.607
Mean Optimism	0.040	0.473	−107.578	0.002	0.067	28.866

Forecast Performance Measures I define the following three absolute forecast performance measures, which only depends on the analyst's own forecast and the true EPS, but not rivals' forecasts. *Forecast Error* is the absolute difference between a forecast EPS and the corresponding actual EPS. It does not differentiate whether an analyst over-estimates or under-estimates. *Optimism Bias* is the difference between a forecast EPS and the corresponding actual EPS. It has a mean of 0.012 in the sample, which implies that on average, analysts over-estimates the earnings. I also define *Absolute Optimism* to be a binary indicating whether analyst i's forecast is above the realized true EPS.

In addition, I define two relative forecast performance measures to capture how an analyst performs relative to her rivals. For security j, analyst i, in period t, I define *Relative Accuracy* by a normalized accuracy rank. N_{jt} denotes the number of analysts making forecast, which I call active analysts. I first rank all active analysts by their *Forecast Error*, 1 for the most accuracy and N_{jt} for the least accurate. Then I normalize the accuracy rank by the number of the active analysts to 100. I also define *Relative Optimism* to be a binary indicating whether analyst i's forecast is above the average forecast in that market-year.

$$RelativeAccuracy_{ijt} = \begin{cases} 100 - \frac{AccuracyRank_{ijt}-1}{N_{jt}-1} \times 100 & \text{if } N_{jt} \neq 1 \\ 50 \quad \text{if } N_{jt} = 1 \end{cases}$$

$$RelativeOptimism_{ijt} = 1 \quad \text{if } Forecast_{ijt} > \bar{Forecast}_{jt}$$

Security There are 817 securities in the sample, i.e., 817 markets. On average, each security is covered by 13 analysts from 12 brokerage firms in one year. We observe that the distribution of the number of covering analysts for a security-year closely resembles that of the number of covering brokerage firms. It implies that there is typically only one analyst from each brokerage firm that covers a security. On the other hand, the total number of analysts having covered a security ranges from 8 to 341 analysts. It is must larger than the number of analysts in one year, because there is a lot of entry and exit in the market. An analyst may decide to not make a forecast on a security for one year and return a year later. Since I restrict the sample to be securities that are present in the dataset for over 20 years for the dynamic analysis, the *Years in Sample* is between 21 years and 34 years.

Analyst There are 13,543 analysts in the sample. *Tenure* is constructed from the number of years an analyst is present in the full data. There are cases where an analyst stop making forecast for a year and then returns to the job. In these cases, the absent period will be included in the *Tenure* if it is less than three years. The *Number of Past Employers* verifies the observation that employment in sell-side research is highly mobile. An analyst has been employed by 3 brokerage firms on average and 18 brokerage firms at the most.

4 Model

I define one security to be one market. In each period, there are $\bar{N}$ analysts in total, where $\bar{N}$ is a constant number across securities and periods. In the market for security j at time t, there are N^*_{jt} incumbents and $\bar{N} - N^*_{jt}$ potential entrants. Incumbent analysts are those who are already making forecast on a given security's earnings per share (EPS) last period. They are long-lived and make intertemporal exit decisions. Potential entrants are drawn from a large pool of short-lived analysts, who base their entry decisions on the net present value of entering today. They do not take the option value of delaying entry. All analysts are subject to discount factor β.

Each period, an incumbent has to decide whether to continue to make forecast on this security, and a potential entrant has to decide whether to start making forecast on a given security. We call analysts who decide to make forecasts "active analysts" and denote their number by N_{jt}. The active analysts observe private signals and choose their forecasts. For notation simplicity, I will describe the model for one market and omit the subscript for security j and time t in the rest of this paper.

At the beginning of each period, analyst i observes state variables ω_i which is composed of her reputation $r_i \in R$, rivals' reputation r_{-i}, the number of incumbents N^*, and the current EPS of the security $s \in S$. A market is characterized by all analysts' reputations and the aggregate state s: $\omega = \{r_1, ..., r_{N^*}, s\} \in \Omega$.[5] I assume three levels of reputation, low l, high h and terminated t, so $R = \{l, h, t\}$. Upon entering, an entrant is randomly endowed a reputation of either low or high. An incumbent can take any of the three levels of reputation. I use ω to denote the state of the market at the beginning this period and ω' to denote the state at the end of this period (i.e., the beginning of the next period).

4.1 Timing

1. Analysts observe the current state ω. Incumbent analysts learn their exit compensations and potential entrants learn their entry costs.

2. Incumbents decide on exit. Potential entrants decide on entry. The entry and exit decisions are implemented immediately. The entrants are randomly endowed with a reputation of either low or high. The incumbents who are terminated leave the market.

3. Incumbents and entrants who stay in the market (active analysts) observe private signals of the EPS they need to forecast. They update their belief about the distribution of next period's EPS.

[5] If we adopt the Bayesian approach, the current EPS should be replaced with this period's prior, which depends on the history and the initial prior but is still just one state variable.

4. Forecasts from active analysts are announced.

5. EPS is realized. Analysts' compensation is realized and their reputations are updated. Exit and entry decisions are implemented.

4.2 Incumbent analysts

Consider an incumbent analyst i. At the beginning of each period, the incumbent analyst draws a random exit compensation ϕ_i from a distribution $F(\cdot)$ with expectation $\mathbb{E}(\phi_i) = \phi$.The exit compensations are i.i.d. across analysts and periods and are private to the analysts.

Analyst i receives a private signal of next period's EPS $\hat{s}_i = s' + \epsilon_i$ where the signal noise e_i is independently drawn from a distribution $G(\cdot)$.I assume the distribution to be $N(0, \sigma)$. Let $\hat{G}(\cdot)$ denote the distribution of $\hat{s}_i$ conditional on current aggregate state s. Let $H_i(\cdot)$ denote the distribution of s' conditional on signal $\hat{s}_i$. If I assume normality on the aggregate state transition from s to s', $\hat{G}$ will be normal as well. Let $\hat{S}$ denote the state space for $\hat{s}_i$.

$\chi_i(\omega, \phi_i) = 1$ indicates that analyst i remains in the market. $\chi_i(\omega, \phi_i) = 0$ indicates exit. Let $\xi_i(\omega) = \int \chi_i(\omega, \phi_i) dF(\phi_i)$ denote the probability of analyst i remaining in the industry in state ω.

If analyst i remains in the market, she receives a fixed wage based on her reputation $\pi_i(r_i)$. In addition, she receives a bonus/incurs a cost $c_i(x, s')$, which depends on analyst i's forecast $x_i \in [0, \bar{x}]$, other analysts' forecasts $x_{-i} \in [0, \bar{x}]^{N-1}$, and the true EPS next period s'. I call function $c(\cdot)$ the bonus function, specified as

$$c_i(x, s') = \gamma_{1i} First_i + \gamma_{2i}(x_i - s')^2.$$

This bonus function captures the immediate compensation that the analyst receives. $First_i$ is a dummy which equals to 1 if analyst i's forecast is closer to the realized earnings than all of its rivals, i.e., $|x_i - s'| < |x_k - s'|$ for all $k \neq i$. In this case, I say that analyst i is the first. γ_{1i} is the reward for being the first. γ_{2i} captures the reward or punishment for having higher forecast errors. I allow the γ's to depend on analyst i's reputation, r_i.

4.3 Potential entrants

Consider a potential entrant i. At the beginning of each period, the potential analyst draws a random entry cost ϕ_i^e from a distribution $F^e(\cdot)$ with expectation $\mathbb{E}(\phi_i^e) = \phi^e$. The entry costs are i.i.d. across analysts and periods and are private to the analysts.

Analyst i also draws a signal of next period's EPS $\hat{s}_i^e = s' + \epsilon_i^e$ where the signal noise ϵ_i^e is drawn from a distribution $G^e(\cdot)$. Let $\hat{G}^e(\cdot)$ denote the distribution of $\hat{s}_i^e$ conditional on current aggregate state s. Let $H_i^e(\cdot)$ denote the distribution of s' conditional on signal $\hat{s}_i^e$. Let $\hat{S}^e$ denote the state space of $\hat{s}^e$.

Again, $\chi_i(\omega, \phi_i^e) = 1$ indicates that analyst i enters the market. $\chi_i(\omega, \phi_i^e) = 0$ indicates that analyst i stays out. Let $\xi_i(\omega) = \int \chi_i(\omega, \phi_i^e) dF^e(\phi_i^e)$ denote the probability of entry of analyst i in state ω. If analyst i enters the market, similar to the incumbents, she receives a bonus based $c_i(x, s')$.

For any $k \neq i$, regardless of their reputations, let $x_{k|i}(\omega) = \int x_k(\omega, \hat{s}_k) d\hat{G}(\hat{s}_k|\hat{s}_i)$ denote the expected forecast from analyst k conditional on analyst i's signal.

4.4 Transition probabilities

The transition probabilities can be represented by the transition function $\mathcal{P} : \Omega^2 \times [0,1]^N \times [0, \bar{x}]^N \to [0,1]$. Thus $\mathcal{P}(\omega, \omega', \chi(\omega, \phi), x(\omega, \hat{s}_i))$ is the probability that the market moves from ω to ω' given analysts' exit and entry decisions $\chi(\omega, \phi)$ and forecast decisions $x(\omega)$.

4.5 An incumbent's problem

$V_i(\omega, \phi_i, \hat{s}_i)$ is defined recursively by the solution to the following Bellman equation,

$$\begin{aligned} V_i(\omega, \phi_i, \hat{s}_i) = & \sup_{\substack{\tilde{\chi}_i(\omega, \phi_i) \in \{0,1\}, \\ \tilde{x}_i(\omega, \hat{s}_i) \in [0, \bar{x}]}} \pi_i(r_i) + (1 - \tilde{\chi}_i(\omega, \phi_i))\phi_i + \tilde{\chi}_i(\omega, \phi_i) \\ & \times \{\mathbb{E}\{c_i(\tilde{x}_i(\omega, \hat{s}_i), x_{-i|i}(\omega), s') + \beta V_i(\omega') | \omega, \hat{s}_i, r_i' \neq e, \tilde{x}_i(\omega, \hat{s}_i), \xi_{-i}(\omega), x_{-i|i}(\omega)\}\} \end{aligned}$$

where $V_i(\omega) = \int \int V_i(\omega, \phi_n, \hat{s}_i) dF(\phi_i) d\hat{G}(\hat{s}_i|s)$ is the expected value function.

Note that $V_i(\omega, \phi_i, \hat{s}_i)$ is the value function after the analyst has drawn the exit compensation and the private signal and $V_i(\omega)$ is the expected value function before the random values are drawn.

The optimal exit decision of incumbent analyst i who has drawn exit compensation ϕ_i is a cutoff rule characterized by

$$\chi_i(\omega, \phi_i) = \begin{cases} 1 & \text{if } \phi_i \leq \bar{\phi}_i(\omega) \\ 0 & \text{if } \phi_i > \bar{\phi}_i(\omega) \end{cases}$$

where

$$\bar{\phi}_i(\omega) = \mathbb{E}\big\{ \sup_{\tilde{x}_i(\omega, \hat{s}_i) \in [0, \bar{x}]} \mathbb{E}\{c_i(\tilde{x}_i(\omega, \hat{s}_i), x_{-i|i}(\omega), s') + \beta V_i(\omega') | \omega, \hat{s}_i, r_i' \neq e, \tilde{x}_i(\omega, \hat{s}_i), \xi_{-i}(\omega), x_{-i|i}(\omega)\}\big\}$$

Then, the exit decision rule can also be represented by $\xi_i(\omega) = F(\bar{\phi}_i(\omega))$. The random exit compensation can be integrated out to obtain

$$V_i(\omega,\hat{s}_i)=\sup_{\substack{\tilde{\xi}_i(\omega)\in[0,1],\\ \tilde{x}_i(\omega,\hat{s}_i^e)\in[0,\bar{x}]}}\pi_i(r_i)+(1-\tilde{\xi}_i(\omega))\phi+\int_{\phi_i>F^{-1}(\tilde{\xi}_i(\omega))}(\phi_i-\phi)dF(\phi_i)+\tilde{\xi}_i(\omega)$$
$$\times\{\mathbb{E}\{c_i(\tilde{x}_i(\omega,\hat{s}_i),x_{-i|i}(\omega),s')+\beta V_i(\omega')|\omega,\hat{s}_i,r_i'\neq e,\tilde{x}_i(\omega,\hat{s}_i),\xi_{-i}(\omega),x_{-i|i}(\omega)\}\}$$

4.6 An entrant's problem

The value function of entrant i given entry cost and private signal is

$$V_i(\omega,\phi_i^e,\hat{s}_i^e)=\sup_{\substack{\tilde{\chi}_i(\omega,\phi_i^e)\in\{0,1\},\\ \tilde{x}_i(\omega,\hat{s}_i^e)\in[0,\bar{x}]}}\tilde{\chi}_i(\omega,\phi_i^e)\times\{-\phi_i^e+\mathbb{E}\{c_i(\tilde{x}_i(\omega,\hat{s}_i^e),x_{-i|i}(\omega),s')$$
$$+\beta V_i(\omega')|\omega,\hat{s}_i^e,r_i'\neq e,\tilde{x}_i(\omega,\hat{s}_i^e),\xi_{-i}(\omega),x_{-i|i}(\omega)\}\}.$$

The entrants are short-lived so they do no solve an intertemporal maximization problem to decide entry.

The optimal exit decision of entrant i who has drawn entry cost ϕ_i is a cutoff rule characterized by

$$\chi_i(\omega,\phi_i^e,\hat{s}_i^e)=\begin{cases}1 & \text{if } \phi_i^e<\bar{\phi}_i^e(\omega)\\ 0 & \text{if } \phi_i^e\geq\bar{\phi}_i^e(\omega)\end{cases}$$

where

$$\bar{\phi}_i^e(\omega)=\mathbb{E}\big\{\sup_{\tilde{x}_i(\omega,\hat{s}_i^e)\in[0,\bar{x}]}\mathbb{E}\{c_i(\tilde{x}_i(\omega,\hat{s}_i^e),x_{-i|i}(\omega),s')+\beta V_i(\omega')|\omega,\hat{s}_i^e,r_i'\neq e,\tilde{x}_i(\omega,\hat{s}_i^e),\xi_{-i|i}(\omega),x_{-i|i}(\omega)\}\big\}$$

Then, the entry decision rule can also be represented by $\xi_i^e(\omega)=F(\bar{\phi}_i^e(\omega))$. The random exit compensation can be integrated out to obtain

$$V_i(\omega,\hat{s}_i^e)=\sup_{\substack{\tilde{\xi}_i(\omega)\in[0,1]\\ \tilde{x}_i(\omega,\hat{s}_i^e)\in[0,\bar{x}]}}-\int_{\phi_i<F^{-1}(\tilde{\xi}_i(\omega))}(\phi_i^e-\phi)dF(\phi_i^e)+\tilde{\xi}_i(\omega)$$
$$\times\{-\phi^e+\mathbb{E}\{c_i(\tilde{x}_i(\omega,\hat{s}_i^e),x_{-i|i}(\omega),s')+\beta V_i(\omega')|\omega,\hat{s}_i^e,r_i'\neq e,\tilde{x}_i(\omega,\hat{s}_i^e),\xi_{-i}(\omega),x_{-i|i}(\omega)\}\}$$

5 Estimation

I extend the two-stage algorithm of BBL to estimate the model. BBL provides a framework to estimate dynamic games where players' behavior is consistent with a Markov perfect equilibrium

(MPE). They assume that the data is generated by a *single* MPE, otherwise, the transition probabilities might be different for different portions of the data and are unidentified.

I propose an extension to their method making use of a particular data characteristic in the sell-side analyst competition: the actual EPS s evolves independent of analysts' reputation and forecasts but it affects analysts behavior in the sample market. Formally, I have the following assumption.

A1 The transition probability of s is independent of analysts' current reputation r, entry and exit decisions χ, and forecasts x.

$$P(s'|r, s, \chi, x) = P(s'|s)$$

Given the model, this assumption is trivially satisfied since s_t follows a Markov process. In reality, analysts do not interfere their subject companies business practices, so this assumption is also natural. I name this type of state variable an *aggregate state variable.* Since an aggregate state variable is a time series and is independent of the actions and the other state variables, its stochastic process can be separately estimated. Then the transition probabilities of the other state variables and the policy functions can be estimated conditioning on the aggregate state variable. This approach allows non-stationary transition of the other state variables, assuming that the non-stationarity is generated by the aggregate state variable. It produces more realistic results in the dynamic environment of this paper.

Now, I will describe the two-stage estimation method in detail.

5.1 First Stage

In the current model, the transition probability of an analyst's reputation not only depends on her own reputation, but also her rivals' reputation. This creates a curse of dimensionality when the number of analysts increases. I make the following assumptions on the transition probability to reduce the dimensionality of the transition probabilities.

A2 The reputation of any analyst *next period* does not affect the reputation transition probability of any other analyst. And the reputation of analyst *this period* does not affect the reputation transition probability of any other analyst beyond the forecasts.

$$\begin{aligned} P(r'|r, s', \chi, x) &= P(r'_{-N}|r'_N, r, s', \chi, x) P(r'_N|r, s', \chi, x) \\ &= P(r'_{-N}|r'_N, r, s', \chi, x) P(r'_N|r_N, s', \chi, x) \\ &= \dots \\ &= \prod_i P(r'_i|r_i, s', \chi, x) \end{aligned}$$

A3 Conditional independence of s: Current period's earnings do not have any dynamic effect beyond the reputation of the analysts this period.

$$P(r'|r, s', s, \chi, x) = P(r'|r, s', \chi, x)$$

With Assumptions A1-A3, the transition function can be simplified as

$$\mathcal{P}(\omega, \omega', \chi(\omega, \phi), x(\omega, \hat{s})) = P(r', s'|r, s, \chi, x) = \prod_i P(r_i'|r_i, s', \chi, x)P(s'|s),$$

where $P(r_i'|r_i, s', \chi, x)$ for all i and $P(s'|s)$ can be estimated separately. The reputation transition probabilities $P(r_i'|r_i, s', \chi, x)$ are estimated with a multinomial logit model, where analysts face a probability of updating their reputation to low, high or terminated, depending on their current reputation, forecasts, the level of competition in the market and the realized true EPS. The transition probability of the EPS $P(s'|s)$ is separately estimated for each market with a time series model. I run a unit root test on each security and then fit an AR(1) process to it if the test is rejected and a unit root process otherwise.

To estimate the policy function, I assume a symmetric equilibrium given the state variables, i.e., $\tilde{\xi}_i = \tilde{\xi}$, and $\tilde{x}_i = \tilde{x}$, for all i. Analysts' forecast policy function $\tilde{x}$ is estimated in a two-step model that is similar to the Heckman's selection model. In the first step, I use an ordered probit model to estimate whether analysts' forecast will be higher than the truth (optimistic), lower than the truth (pessimistic), or at the truth (zero). In the second step, for forecasts that are optimistic or pessimistic, I compute their forecast errors and fit a generalized linear model with a logarithm link. The explanatory variables in both steps include all the state variables as well as the realized EPS, and I allow the shocks in the two steps to be correlated. Finally, I estimate the entry and exit probabilities $\tilde{\xi}$ with logit models and allow them depend on the level of competition, all analysts' reputation, as well as the true EPS.

5.2 Second Stage

I use simulated method of moments to estimate the model. The algorithm is described as follows.

Step 1. Estimate the transition probabilities of the aggregate state variable s.

Step 2. Estimate the transition probabilities of other state variables and the policy functions, which are allow to depend on the realized aggregate state variable next period s'.

Step 3. For each observation with reputation r, realized EPS s', and number of active analysts N, simulate entries, exits and forecasts, and update analysts' reputation following the first stage estimates.

Step 4. Repeat Step 3 for nt periods and for ns paths.

Step 5. Construct the value function at observed forecasts x_i.

Step 6. Perturb the observed forecasts slightly to obtain $x_i + \epsilon$ and repeat Step 3 to 5 with the same starting states (r, s', N) and the perturbed forecasts.

Step 7. Repeat for all observations. Use the value functions at the observed forecasts and the perturbed forecasts to construct numerical first order conditions at the observed forecasts for the dynamic problem.

Step 8. Choose model parameters such that the numerical first order conditions are equal to zero.

In particular, I use the first order conditions at the observed forecasts as the moment conditions, which are equal to zero if the observed forecasts are optimal. Note that analysts' forecast decisions depend on their private signals which are unobservable to the econometrician. To resolve this issue, I assume that for any given state variables, analysts' forecasts are a bijective function of analysts' signals, so we can invert analysts' forecasts to obtain their signals. In practice, I estimate the realized EPS as a linear model of analysts' state variables and their forecasts with analyst fixed effects. Then, I use the predicted realized EPS as each analyst's posterior of the true EPS after receiving their private signals, i.e., $\mathbb{E}(s'|\hat{s}_i)$. This posterior enters as analysts' privates signals in the simulation. Finally, to improve the estimation efficiency, I use the following instruments which are uncorrelated with first order conditions to construct additional moments: analysts' reputation, the number analysts at different reputation levels, the first to the seventh lags of the truth, and analysts' posterior of the truth.

6 Results

In this section, I will first discuss some results from the first stage that highlight analysts' strategic incentives, and then discuss the second stage results.

6.1 First Stage

Table 2 presents the reputation transition probabilities. The first (last) two columns show how the level of competition and analysts' forecast performance affect analysts' probability of receiving high (terminated) reputation in the next period, for low-reputation and high-reputation analysts. First, I find that reputation is persistent: all else equal, low-reputation analysts are much less likely receive high reputation than high-reputation analysts as indicated by a smaller intercept. Second, I find that higher relative accuracy significantly increases the probability for all analysts to receive high reputation, which implies that analysts may face incentives to outperform their rivals. Third, high-reputation analysts are significantly less likely to maintain their high reputation if their forecast errors are high, whereas low-reputation analysts' probability of receiving high-reputation is not affected by their forecast errors. This could suggest that low-reputation analysts

Table 2: Reputation Transition Probability

Variables	Low→High	High→High	Low→Termt	High→Termt
Intercept	-1.332***	3.346***	-1.915***	0.848***
	(0.292)	(0.226)	(0.275)	(0.302)
Log No. Competitors	0.084**	0.015	0.481***	0.096
	(0.036)	(0.048)	(0.035)	(0.064)
Log No. High-rep Competitors	-0.066***	-0.228***	-0.070***	0.130**
	(0.010)	(0.043)	(0.009)	(0.058)
Relative Accuracy	0.074**	0.258***	-2.218***	-2.182***
	(0.034)	(0.035)	(0.035)	(0.048)
Forecast Error^2	0.008	-0.031***	0.031***	0.011
	(0.015)	(0.010)	(0.009)	(0.010)
Relative Optimism	-0.055**	0.019	0.114***	0.122***
	(0.022)	(0.022)	(0.023)	(0.031)
Absolute Optimism	-0.014	-0.106***	0.237***	0.271***
	(0.023)	(0.024)	(0.024)	(0.033)
EPS	-0.012	0.055***	-0.032***	0.010
	(0.011)	(0.010)	(0.010)	(0.014)
No. Observations	114408	101679	114408	101679

Standard errors in parentheses. Correlated random effect at the market level included.
*** p<0.01, ** p<0.05, * p<0.1

face more incentive to outperform their rivals than high-reputation analysts. However, one can also observe that forecast errors affect low-reputation analysts' probability of being terminated. So overall, whether low-reputation analysts face more reputational incentive to outperform their rivals will depend on the wage difference between the three reputation levels. In summary, the transition probabilities show that analysts face strategic incentives to outperform their rivals and those incentives may differ depending on their reputation.

Table 3: Forecast Policy Function

Variables	Ordered Probit	Log Error
Log No. Competitors	0.267***	0.193***
	(0.016)	(0.024)
Low-rep.	-0.032	-0.092**
	(0.029)	(0.044)
Log No. Competitors X Low	-0.026	0.182***
	(0.017)	(0.024)
Log No. High-rep Competitors	-0.098***	0.206***
	(0.015)	(0.020)
Log No. High-rep Competitors X Low	0.070***	-0.199***
	(0.015)	(0.020)
EPS	-0.228***	-0.087***
	(0.003)	(0.004)
Pessimistic|Zero	0.961***	
	(0.064)	
Zero|Optimistic	1.188***	
	(0.064)	
Correlation of Shocks		0.066***
		(0.004)
No. Observations	216087	198421

Standard errors in parentheses, clustered at market-year level for Log Error.
Market FE included. Analyst FE included for Log Error.
*** p<0.01, ** p<0.05, * p<0.1

Table 3 presents the forecast policy function. The coefficients of the ordered probit model are presented in column 1, which determines whether a forecast is optimistic or pessimistic. The coefficients of the generalized linear model is presented in column 2. First, we find that analysts are more likely to be optimistic when they face more competition, as indicated by the positive coefficient on the log number of competitors in the first column. Also, this effect is less pronounced if the competition comes from high-reputation rivals. Second, analysts have higher forecast errors when they face more competition and the effect is bigger for low-reputation analysts. This suggests that low-reputation analysts may face more strategic incentive to outperform their rivals.

Table 4: Analyst's Payoff Function

Reputation	Wage	First	Forecast Error^2
Low	1.471***	-0.334	0.013
	(0.668)	(0.283)	(0.079)
High	2.357***	-0.086	-0.048
	(0.698)	(0.394)	(0.086)

Notes: Bootstrap standard errors based on 100 simulations.

6.2 Second Stage

Table 4 presents the parameter estimates of analysts' wage and bonus function. The wage of terminated analysts is normalized to 0. I find that high-reputation analysts receive 1.6 times the wage of low-reputation analysts. This implies that analysts face strong reputational incentives when they issue forecast, as their forecast performance significant affect their probability of receiving high-reputation. Meanwhile, I find that the bonus analysts receive are not significantly affected by their forecast performance. These results imply that analysts are driven more by long-term reputational incentives rather than short-term compensation when they issue forecasts.

7 Conclusion

This paper studies the dynamic competition between sell-side analysts. I find that analysts' incentives to outperform their rivals may lead to them to distort their forecasts (e.g., by issuing bold forecasts) and result in higher forecast errors. Moreover, these incentives mostly come from long-term reputation building motives rather than short-term bonus earning motives.

The contribution of this paper is two-fold. First, it is the first to estimate the dynamic competitive effect of reputation acquisition, in the context of the sell-side research market. It builds and estimates a structural model where analysts decide whether to cover a security and make forecasts on securities' earnings to acquire reputation. The model disentangles to what extent security analysts' are incentivized by the long-term reputation acquisition motive vs short-term bonus earning incentive. One limitation of the paper is that analysts' compensation is not unobserved in reality, and the identification between the long-term and short-term incentive come entirely from analysts' forecasts and reputation within the sell-side industry, which may be noisy and fail to explain some of the heterogeneity in payoff. For example, some terminated analysts may have gone to well-compensated buy-side firms, which creates heterogeneity the payoff of terminated analysts. Future research can supplement this analysis by incorporating analysts' compensation data.

Second, it develops a methodology for estimating a dynamic competition where analysts' strategy changes overtime. It extends BBL's two-stage algorithm by including an aggregate state variable whose transition is not affected by other state variables or analysts' action. This methodology could potentially be used to study other dynamic games where players' strategy is non-stationary but controllable through an aggregate state variable. An example could be an industry with an upstream market and a downstream market, as in Eizenberg (2014). In Eizenberg (2014), innovation in the CPU market affects discrete product choices in the down stream PC market.

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A Entry and Exit Probabilities

Table 5: Entry and Exit Probability

Variables	Entry	Endowed with High Rep.	Exit from Low	Exit from High
Log No. Competitors	-0.107***	0.150	1.706***	-0.936***
	(0.038)	(0.111)	(0.126)	(0.178)
Log No. High-rep Competitors	0.251***	0.268***	-0.263***	1.859***
	(0.013)	(0.042)	(0.028)	(0.137)
Log No. Term. Competitors	0.105***	0.013	0.054***	0.070***
	(0.006)	(0.017)	(0.013)	(0.014)
EPS	0.077***	0.021	-0.324***	-0.206***
	(0.018)	(0.050)	(0.041)	(0.040)
No. Observations	16254	13199	15542	14440

Standard errors in parentheses. Market FE included.
*** p<0.01, ** p<0.05, * p<0.1

The entry and exit probabilities are presented in Table 5. I find that analysts are less likely to enter into securities with a lot of competition in general but more likely to enter if the competition comes from high-reputation analysts (column 1). Moreover, low and high-reputation analysts exhibit opposite exit patterns when they face more competition: low-reputation analysts are more likely exit when there is more competition, whereas high-reputation analysts are less likely to exit. Both are more likely to exit when the competition is coming from analysts of their own reputation. Finally, analysts are more likely to enter and less likely to exit when the EPS is high, that is, the security is likely performing well.