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Fool's Gold: Social Proof in the Initiation and Abandonment of Coverage by Wall Street Analysts

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This paper examines the dynamics of social influence in the choices of securities analysts to initiate and abandon coverage of firms listed on the NASDAQ national market. We show that social proof—using the actions of others to infer the value of a course of action—creates information cascades in which decision makers initiate coverage of a firm when peers have recently begun coverage. Analysts that initiate coverage of a firm in the wake of a cascade are particularly prone to overestimating the firm's future profitability, however, and they are subsequently more likely than other analysts to abandon coverage of the firm. We thus find evidence for a cycle of imitation-driven choice followed by disappointment and abandonment. Our account suggests that institutionalization rooted in imitation is likely to be fragile.•

A core proposition in organizational theory is that imitation is a characteristic response to uncertainty in decision making (Cyert and March, 1963). Imitation follows from the heuristic of social proof, that is, looking to the actions of others for clues as to what constitutes appropriate action (Cialdini, 1993). Neoinstitutionalist theory holds that decision makers imitate peers, especially peers perceived to be successful and legitimate, to minimize search costs and to avoid the costs of experimentation (DiMaggio and Powell, 1983). If a practice is prevalent among competent actors, then it must be sensible. But neoinstitutional research also presumes a model of human behavior in which people persist in a course of action that they have copied from others even when it is against their own interests. Such a model implies that actors are cognitive dopes rather than cognitive misers. Cognitive dopes blindly follow others and stick to a course of action, whereas cognitive misers use heuristics to reduce search costs but are quite capable of abandoning a choice in light of new evidence about its value (Fiske and Taylor, 1991).

Reliance on heuristics such as social proof can often lead to overvaluation of the choice and regret about the decision, and the cognitive miser model may therefore be a more realistic description of the dynamics of adoption of a practice. Organizations routinely adopt programs intended to improve performance, such as quality circles, only to abandon them when the programs fail to live up to their promise (Abrahamson and Fairchild, 1999), resulting in waves of adoption and abandonment (Barley and Kunda, 1992). Even hybrid corn, the canonical setting for understanding the adoption of innovation since the work of Ryan and Gross (1943), did not diffuse once and for all. Apodaca (1952) found that the percentage of adopters in a population of New Mexico farmers rose from 0 to 60 percent between 1945 and 1947 but fell back to 3 percent by 1949. The wet-kiln process of mixing cement was mimetically adopted and came close to replacing the dry-kiln process in the U.S. cement industry but later fell out of favor and was widely abandoned (Anderson, 1999). Recently, matrix structures have been adopted and abandoned (Burns and Wholey, 1993), and conglomerates have been built and disassembled (Davis, Diekmann, and Tinsley, 1994). Thus, imitation-based institutionalization appears to be fragile empirically because social proof triggers adoptions that are later judged to be erroneous: hybrid corn tasted bad, the

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wet-kiln process wasted energy, matrix organizations were complex, and conglomerates were inefficient. Once adopters have updated their information based on their own experience, they can abandon a course of action if their decision to adopt was not irrevocable in the first place.

Neoinstitutionalists rarely study adoption and abandonment decisions concurrently because they examine courses of action that have either diffused widely or been abandoned wholesale—a form of selection bias (Strang and Soule, 1998). Yet it is clear from the examples above that adoption is sometimes followed by regret and abandonment: the more highly one evaluates an uncertain course of action ex ante, the more likely one is to be disappointed. To the extent that adoption is based on imitation, we should expect to see overvaluation, disappointment, and abandonment. We explore this idea by studying how equity analysts employed by investment banks initiate and cease coverage of the securities of firms listed on the NASDAQ stock market. Analysts evaluate the prospects of securities issuers and render both summary judgments (recommendations to buy, hold, or sell shares) and regular estimates of expected earnings (Zuckerman, 1999). Thus, analysts make choices of whether to add or drop a firm from the portfolio of firms they cover and judgments of the firms' expected profitability. Analysts typically specialize by industry, and limits on time and energy mean that they must be selective in which firms they choose to follow. Incentives in investment banks favor covering firms whose stock market performance is expected to be good in the future and avoiding poor performers, and analysts are punished for being inaccurate in their earnings forecasts (Hong, Kubik, and Solomon, 2000). Yet predicting which firms will be winners is an impossible task, according to the efficient market hypothesis, which suggests that future price movements follow a random walk pattern; thus, "financial forecasting appears to be a science that makes astrology respectable" (Malkiel, 1996: 169). In this context of extreme uncertainty, selecting which firms to follow in one's portfolio is a plausible context for mimesis. It is also an appropriate context for enhancing our understanding of institutionalization by studying adoption, evaluation, and abandonment dynamically.

We focus on the initiation and cessation of coverage by securities analysts because these decisions constitute instances of adoption and abandonment. The initiation of coverage means that the research department employing the securities analyst has decided to adopt the focal organization as a subject for study and to allocate resources to its research. We also examine the impact of mimesis-based adoption on the propensity to overestimate earnings and the effects of earnings overestimates and mimesis-based adoption on subsequent abandonment. By studying the complete cycle of adoption, evaluation, and abandonment, we provide a more complete perspective on processes of institutionalization.

SOCIAL PROOF, CASCADES, AND POSTDECISION REGRET

The literature in social cognition suggests that there are two routes to persuasion: a central route of systematic processing of information and a peripheral route of heuristics or cognitive shortcuts (Petty and Cacioppo, 1986). Actors engage in systematic processing when they have the capacity to do so and are motivated by accuracy motives, and they rely on heuristic processing to reduce search costs (Fiske and Taylor, 1991). Social proof is a heuristic by which we "view a behavior as correct in a given situation to the degree to which we see others performing it. Whether the question is what to do with an empty popcorn box in a movie theater, how fast to drive on a certain stretch of highway, or how to eat chicken in a restaurant, the actions of those around us will be important guides in defining the answer" (Cialdini, 1993: 95). Social proof is most influential when decision makers are uncertain about the value of a course of action and when they are able to observe the actions of similar others.

Rational choice theorists have created stylized models of how the heuristic of social proof produces information cascades when actions are sequential and decision makers learn by observing the actions of others rather than through verbal communication (e.g., with managers of competing firms; see Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992). Models of information cascades typically assume that decisions are discrete and observable—to invest or not to invest, to adopt or to reject—but that the values of outcomes for the decision makers are unobservable. Consider an example in which risk-neutral individuals sequentially decide whether to adopt or reject an action. The payoff to adopting, V, is either 1 or –1 with equal probability; the payoff to rejecting is 0. In the absence of further information, both alternatives are equally desirable. Each individual has access to information that results in a private evaluation of either high or low, and high is more likely if adoption is desirable than when it is undesirable (we use the shorthand "observes high" when the individual has information that gives an evaluation of high). Each individual observes high with probability $p > 1/2$ if $V = 1$, and with probability $1 - p$ if $V = -1$. Calculation using Bayes' rule shows that after observing high, an individual's posterior probability that $V = 1$ is p and the probability that $V = 1$ is only $1 - p$ if he or she observes low. Thus, p is the (posterior) probability that the signal is correct (Bikhchandani, Hirshleifer, and Welch, 1998). The first decision maker, A, adopts if his or her signal is high and rejects if it is low. All successors can infer A's signal from his or her action: if A adopted then he or she must have observed high, and if A rejected, he or she must have observed low. The second decision maker, B, has two signals, the one inferred from A's action and his or her own private signal. If B's signal agrees with A's action, he or she will adopt. If B's signal is contrary, then he or she is indifferent between adopting and rejecting and can toss a coin to decide. The third decision maker, C, can confront two possible situations: both predecessors made the same decision (adopt or reject), or one adopted and the other rejected. If both predecessors made the same decision, the weight of the evidence favors imitation even if the private signal is contradictory. This is true even though C knows that B may have imitated A, since the probability that B chose based on a signal consistent with A's is greater than the probability that B chose based on a contrary signal. When C sees two adoptions of the same action, he or she is in an information cascade, because his or her action does not reflect his or her private information. Everyone after C faces the same decision and adopts based only on the observed actions of predecessors. If the two predecessors of C made different decisions, then C will follow his or her own signal, and D will then observe two adoptions of one alternative, one of the other, and have a private signal. Again, a majority rule will decide, and a coin flip can be used to break a tie. This model can result in many different adoption sequences depending on the information seen by each actor, but nearly all of these reach a tipping point, after which no additional information accumulates. The more adoptions that have been made, the more likely it is that the tipping point has been reached.

This simple model of an information cascade yields testable predictions about the behavior of actors who choose among alternatives in an uncertain environment in which the actions of others are observable. First, the adoption of one alternative becomes more likely the more others have made the same choice. Second, the marginal effect of each additional prior adopter will decline because the new information revealed by each additional adopter is lower when many have adopted earlier. Third, the actors' evaluations of an alternative are higher the more others have chosen it. Since the evaluations increase with the number of prior adopters but the true value does not, it follows that overevaluations become more likely when many prior adopters are found. Fourth, if the true value is revealed after adoption, then disappointments are more likely for those who adopt after many others. Indeed, if many adopt the same alternative, and thus receive the same true value, it is likely that the later adopters become more disappointed, since their subjective evaluation was higher.

This model can be applied to the situation that securities analysts face in their choice to follow firms. At a time when firms are largely owned by institutional investors with portfolios containing several hundred firms, securities analysts review the glut of information about firms and generate summary judgments. These judgments take two main forms: a recommendation of whether to buy, hold, or sell a security and a future earnings forecast indicating how profitable the firm is expected to be, in the form of a quarterly estimate of expected earnings per share. Coverage initiation decisions are usually announced when the analyst issues an earnings estimate for the focal firm and a recommendation; thus, these actions are visible to other analysts that follow the firm or might do so. Abandonment decisions are also known when the analyst stops issuing estimates and recommendations.

Coverage decisions are consequential for the firms that are followed. The initiation of coverage by an analyst increases the stock price of firms with small analyst followings (Branson, Guffey, and Pagach, 1998). When many analysts cover a firm, it gets to be on the radar screen of investors, enjoys increased market valuation, and can raise capital at low cost (Useem, 1996). Conversely, when firms lose coverage from existing analysts, their market values may decline. While the decision to adopt the firm for coverage entails some public commitment on the part of the research department, abandonment of coverage does not injure the reputation of the research department as much as it harms the focal firm.

Research in accounting indicates that analysts initiate coverage when they are optimistic that the value of a security will go up and that pessimism is a precursor to stopping coverage (McNichols and O'Brien, 1997). Analysts' propensity to follow securities perceived as winners with a promising future is indicated by the fact that far less than 5 percent of analysts' recommendations are to sell (rather than to buy or hold). The best sign of an analyst's optimism is his or her earnings forecasts: optimists will issue high forecasts relative to their peers. But inaccuracy in forecasts, when estimates of earnings per share diverge from the actual earnings per share, is costly to the analyst. Mikhail, Walther, and Willis (1999) found that analysts were likely to change jobs if their forecast accuracy declined. Hong, Kubik, and Solomon (2000) showed that analysts, especially inexperienced analysts, were fired for bold forecasts that deviated from the consensus. And Hong, Kubik, and Solomon (2001) reported that analysts with poor past forecast performance also slid down the brokerage house hierarchy. Thus, analysts' coverage choices are consequential, visible, and subject to considerable uncertainty. Social proof goes a long way toward reducing that uncertainty.

Social Proof, Information Cascades, and Adoption

According to the model of information cascades described above, when the consequences of an adoption may be difficult to observe, prospective adopters look at the number of peers adopting an innovation as a clue to what is appropriate. The number of total adopters has been found to influence the adoption of multidivisional forms (Fligstein, 1991; Palmer, Jennings, and Zhou, 1993), matrix management (Burns and Wholey, 1993), curricular change in liberal arts colleges (Kraatz, 1998), ordaining women (Chaves, 1996), and strikes (Conell and Cohn, 1995). Recent adoptions are especially likely to induce cascades because they are accessible and vivid (Tversky and Kahneman, 1974). They are also more relevant to judging the current value of a given innovation, since the value of an innovation can change over time (e.g., a firm's prospects). Thus, the strongest test of social proof is whether recent adoptions increase the rate of subsequent adoptions.

It is also useful to consider whether individual adopters differ in social status and credibility. When high-status individuals or fashion leaders are the first to adopt, cascades may form instantly, because other potential adopters attribute expertise to the fashion leaders and follow them even if their private signals are contrary (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992). Neoinstitutional theory emphasizes the salience of role models (DiMaggio and Powell, 1983) and holds that the actions of high-status peers are cues that enable prospective adopters to view the behavior in question as less risky, more appropriate, and sensible. In a complementary vein, rational-choice accounts suggest that high-status firms may be perceived to possess expertise, so that their adoption decisions are more diagnostic of the true value. Hence, as high-status actors adopt a behavior, other actors follow suit (Burns and Wholey, 1993; Haunschild, 1993; Haveman, 1993; Davis and Greve, 1997; Strang and Soule, 1998). Thus, recent adoptions and recent adoptions by high-status actors make a firm attractive to other analysts and increase the rate at which it attracts new coverage:

Hypothesis 1 (H1): Recent adoptions and recent adoptions by high-status actors of a focal firm will increase the subsequent rate of coverage initiation by new analysts.

Social Proof and Error

While cognitive heuristics allow one to economize on search costs, they also lead to errors. Cialdini (1993: 131–132) stated that the heuristic of social proof presumes that "if a lot of people are doing the same thing, they must know something we don't. Especially when we are uncertain, we are willing to place an enormous amount of trust in the collective knowledge of the crowd. [But] quite frequently the crowd is mistaken because they are not acting on the basis of any superior information but are reacting, themselves, to the principle of social proof." Early social psychologists, such as Asch (1952), showed that subjects copied the mistaken evaluations made by others. Reliance on social proof can lead to errors in several ways. It can generate pluralistic ignorance, in which inaccurate representations of collective opinion lead decision makers to undertake a wrong course of action (Katz and Allport, 1928). In their famous study of bystander apathy, Latane and Darley (1968) showed that bystanders in a group of apparently unconcerned others are less likely to help in an emergency than if they were alone, because they infer the situation from the actions of others around them. If the other people in the group are also presenting a façade of unconcern, the bystander will incorrectly interpret their appearance of unconcern as a sign that there is no emergency. Thus, behaviors may be perpetuated because individuals are acting based on information imputed to others instead of on their own information.

The winner's curse, in which the bidder willing to pay the highest price at an auction is thereby the one most likely to overvalue the item, can also be explained by reference to social proof. Earlier bids can be interpreted as revealed evaluations of the item's value, leading bidders to adjust their evaluations upward and causing the winner to pay too much. Such bias can be avoided by realizing that other bids are affected by each other and adjusting downward, which is a difficult cognitive task. Kagel and Levin (1986) found that inexperienced decision makers in an auction experiment bid too much, and even experienced decision makers had difficulty making correct bids if the environment changed, such as if a different number of bidders participated. Neeman and Orosel (1999) also showed that sequential-bid auctions produce cascades and winner's curses. In the case of analysts, social proof may induce them to be overly optimistic about the value of a stock and overestimate the firm's earnings prospects:

Hypothesis 2 (H2): Recent adoptions and recent adoptions by high-status actors of a focal firm at the time a focal analyst initiated coverage will increase overestimation errors by the focal analyst for that firm.

Social Proof, Errors and Postdecision Regret

When the heuristic of social proof leads decision makers to commit overvaluation errors, they experience postdecision regret. Postdecision regret is a special form of dissonance in which decision makers wish they had chosen otherwise, even if the decision appeared to be the right one at the time it was made (Loomes and Sugden, 1982; Bell, 1982).[1] Decision makers are exposed to the risk of postdecision regret not because they are uninformed or analytically deficient or because the world is cruel, but simply because choices based on uncertain evaluations lead to overly high expectations (Harrison and March, 1984: 38). Decision makers are particularly likely to encounter postdecision regret when they have high expectations prior to the adoption decision (Simonson, 1992). In our context, a greater number of recent adopters implies that an information cascade is likely to have occurred. This leads to high predecision expectations, subsequent postdecision regret, and pressure toward abandonment, such that the analysts who adopted a firm in the wake of a cascade are more likely to be disappointed and to abandon the firm.

The power of social proof is amplified by the status of the adopter, but the probability of error is amplified as well (Cialdini, 1993). Pluralistic ignorance can ensue when members of a group are misled by visible actors into believing that their own opinions are less widely shared than they actually are. The result is a perceived group opinion that is not representative of the actual attitudes of the group members (Weick, 1979). If all actors are equally informed, attraction to high-status actors increases errors by reducing the number of signals observed by a given actor. Such individual behavior is also likely to occur in organizations unless procedural safeguards are in place. Designers of judicial systems recognize that reliance on high-status actors may lead to errors and strive to minimize such reliance; for instance, in U.S. Navy courts-martial, judges vote in inverse order of rank order to mitigate the influence of higher-ranking judges (Bikhchandani, Hirshleifer, and Welch, 1998). In business organizations, such safeguards are less well known. When safeguards are absent, as they are for analysts, actors are prone to errors caused by status-mediated social proof.

Hypothesis 3 (H3): Recent adoptions and recent adoptions by high-status actors of a focal firm at the time a focal analyst initiated coverage increase the rate of abandonment of coverage.

Hypothesis 4 (H4): Overvaluation errors of a focal firm by a focal analyst increase the rate of abandonment of coverage.

1
Note that satisfaction is different from regret but causally related to it. Satisfaction concerns outcomes, but regret concerns choices. One can be dissatisfied with an outcome and, as a result, regret the choice that led to it (Oliver, 1980).

Mimesis of Abandonment

Just as analysts may look to peers to infer the value of adopting a course of action, they may also find the abandonment of courses of actions by peers informative. Although less studied than positive diffusion, there is some evidence for such negative diffusion. The greater the number of recent abandonments of a course of action, the more likely is post-decision regret to be intensified for current adopters and the more likely are they to abandon. Greve (1995) found that radio stations discontinued the use of the easy listening format when others also abandoned the format. Rao, Davis, and Ward (2000) reported that corporations listed on the NASDAQ stock market were more likely to relist on the New York Stock Exchange when their peers had done so. In both cases, uncertainty about the value of a focal course of action persisted even after adoption, leading to reevaluation and abandonment as a response to observing others abandon it.

Hypothesis 5 (H5): Recent abandonments and recent abandonments by high-status actors of a focal firm increase the subsequent rate of abandonment of coverage.

METHODS

Our initial sample of firms included all 2,020 firms listed in the National Issues Market of NASDAQ in 1987, with a window of observation from 1987 to 1994. We studied NASDAQ firms because they are growth firms that occupy an important position in the American economy. Compared with older and more established firms, such as those listed on the New York Stock Exchange (NYSE), the gain and loss of analyst recognition is more consequential for NASDAQ firms. They are also more uncertain investment prospects and may give rise to stronger information cascades than NYSE firms would. We consulted the IBES database, which contains the most comprehensive information on analysts following firms, to select our analyst sample. Since not all NASDAQ firms are in the IBES database, we selected those firms for which information was available in the IBES database. Thus, firms that were not covered by IBES analysts during our sample period were not included in the sample. This creates a selectivity problem in the analysis of adoptions, for which we control (see below), and our analyses of overestimation of earnings and of abandonment are conditioned on coverage. NASDAQ firms were dropped from the sample when they were liquidated or absorbed by another firm.

Variables

Adoptions. It is not meaningful to treat all investment banks or analysts as being at risk of initiating coverage of a firm, because no one has the resources to cover all the firms on the NASDAQ stock market. Accordingly, in our adoption analyses we treated the NASDAQ firm as the unit of observation and modeled the rate at which firms attracted new analysts. Analysts occasionally initiate coverage because they are taking the place of a previous analyst employed by the same brokerage firm, rather than because of something about the firm or the analyst. We therefore distinguished between coverage initiation (added coverage), when an analyst started issuing recommendations on a focal NASDAQ firm, and new coverage initiation, when an analyst added coverage of a firm when no other analyst in the same brokerage firm had dropped the firm. We split the spells annually to update covariates.

Recent adoptions were measured as the natural logarithm of the number of analysts initiating coverage in the previous year. We logged this variable because we anticipated that the pressure toward mimesis would increase at a decreasing rate (e.g., formula 1 in Bikhchandani, Hirshleifer, and Welch, 1992: 997). *Recent adoptions by high-status actors* were recent adoptions weighted by the status of the research department employing the analyst. We derived the status of research departments from the "All-America Research Team" rating issued by *Institutional Investor* magazine, which is the most widely watched rating in the industry. Each year *Institutional Investor* lists the top ten analysts said to excel in each of the four areas of stock picking, earnings estimates, written reports, and overall service. While some of these criteria are subjective, analysts listed by *Institutional Investor* do have higher precision in earnings estimates than other analysts (Taylor and Clement, 1999), and the selectivity of this ranking makes it a sought-after mark of distinction. We summed a research department's annual number of mentions in the four categories and used the sum to weight the number of recent adoptions by the status scores of each research department. Since most research departments have no all-America team members and thus get a weighted score of zero, these weighted scores reflect the behaviors of the most prominent departments. We logged this variable (adding one before logging). These independent variables were lagged by a year.

We included a number of annually updated control variables thought to affect analysts' coverage decisions. Recent abandonments were measured as the natural logarithm of the number of analysts stopping coverage in the previous year, and recent abandonments by high-status actors were measured using the same weights as for adoptions. The total number of adoptions was measured as the number of analysts currently following the firm, and total number of adoptions weighted by status was also included as a control. Since analysts are interested in large and high-performing firms, we controlled for the average market value of the firm and its market-adjusted stock returns. The firm's stock returns were adjusted by subtracting the NASDAQ Composite market's cumulative return for a given year using a buy-hold strategy for each year. Since analysts prefer not to be surprised by low performance, we computed the firm's uncertainty in performance, which was measured as the standard deviation of daily returns (multiplied by 100 for scaling). A daily return is the percentage appreciation or depreciation in the stock value over a single day, and the standard deviation was computed using data on the price of stock for every stock-trading day of a year. These data were obtained from the CRSP tapes and updated annually. Because institutional shareholders create demand for analyst services (O'Brien and Bhushan, 1990), we included data on the percentage of institutional shareholdings from the SPECTRUM database. Institutional shareholders were defined as banks, pension funds, insurance companies, and mutual funds. We included the number of market makers for a firm's stock because, in dealer-based exchanges such as the NASDAQ, more actors willing to buy and sell a firm's stock from their own portfolio give it greater liquidity and investor recognition, which in turn may attract analysts to it. Because analysts often specialize by industry and industries vary in their attractiveness to investors, we also included the total analyst following of the focal industry, delineated by the two-digit Standard Industrial Classification (SIC) code.

Unfortunately, some NASDAQ firms are missing even from the most comprehensive analyst database (Rajan and Servaes, 1997). Since only 1,442 of the 2,020 NASDAQ firms are included in the IBES database, a sample-selection problem exists. To correct for the selectivity effect, we applied Lee's (1983) generalization of Heckman's (1979) two-stage estimator by estimating a selectivity model and using a selection variable derived from it as an instrument in the regression equation. We took all 2,020 firms in NASDAQ and estimated a logit model with inclusion in IBES as the dependent variable and market value, number of shares outstanding, board size, volume of shares traded, number of market makers dealing with the firm on the NASDAQ exchange, log of bid price, and bid-ask spread as independent variables. These variables have been found to affect inclusion in the IBES dataset (O'Brien and Bhushan, 1990). We used the logit results to compute an instrumental variable λ according to Lee's formula:

$$\lambda = \phi[\Phi^{-1}(F(\beta y))] \,/\, F(\beta y)$$

Here, F is the logit distribution function, Φ is the normal distribution function, and ϕ is the normal density function.

Table 1 displays the descriptive statistics. Most correlations range from small to moderate. We computed variance inflation factors to examine multicollinearity and found that all variables had variance inflation factors well below the usual warning level of 10. The highest variance inflation factor was 4.85 for the add-coverage data set, and 3.61 for the drop-coverage data set.

Adoption of coverage can be modeled either as a count of adoptions during a time interval or as a continuous-time rate of being adopted. Because we had exact (to the day) adoption times of coverage, we took advantage of this precision in the data by using a partial likelihood (Cox) model of the rate of obtaining new coverage. This approach is similar to work on founding rates of firms, which has used rate models of founding events when exact times were available (Hannan and Freeman, 1988). Each observation is a firm, and the observation has a duration from the time of the previous adoption to the next adoption or the data-censoring time (end of study or firm listing at NASDAQ). Observations were split annually to update covariates, and left-censored observations were omitted. One model used coverage initiation as the

Table 1

Descriptive Statistics and Correlation Coefficients for Adoption of Coverage

Variable	Mean	S. D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Added coverage	0.643	0.479														
2. New coverage	0.436	0.496	.65													
3. Market value	645.13	1549.83	.14	.06												
4. Market returns	0.100	0.586	.07	.09	.02											
5. Variance returns	0.130	0.442	–.14	–.08	–.06	–.02										
6. Institutional ownership	36.05	21.92	.27	.16	.22	.08	–.16									
7. Analysts covering industry	1762	1350	.08	.01	.07	–.01	–.06	.03								
8. Market makers	16.537	10.121	.25	.11	.47	.01	–.07	.41	.10							
9. λ	0.204	0.163	–.33	–.18	–.40	–.03	.22	–.44	–.20	–.50						
10. Log analyst coverage	1.874	0.892	.40	.18	.42	–.04	–.20	.55	.13	.67	–.72					
11. Log coverage weighted by status	0.934	1.065	.29	.13	.30	.03	–.10	.35	.06	.45	–.50	.61				
12. Log adoption	1.000	0.681	.47	.41	.22	.19	–.15	.36	.05	.34	–.44	.48	.40			
13. Log adoption weighted by status	0.512	0.827	.20	.11	.05	.06	–.07	.21	.01	.20	–.29	.35	.74	.33		
14 Log abandonment	1.119	0.739	.37	.21	.30	–.01	–.16	.47	.06	.56	–.52	.76	.50	.53	.32	
15. Log abandonment weighted by status	0.533	0.895	.20	.09	.20	–.01	–.07	.27	.06	.38	–.36	.46	.48	.29	.42	.39

dependent variable, and the other used new coverage. We used the latter analysis to ensure that the results were not affected by replacement of the responsible analyst within brokerage firms. In both analyses, we computed robust standard errors adjusted for clustering at the firm level. We used the most recent version of the stcox routine in the Stata package to estimate the models.

Overestimation errors. Since analysts currently following a firm are at risk of making erroneous estimates of the earnings per share of a firm, the analyst-firm dyad year constitutes an observation in the analysis of overestimation errors. An error was defined as an analyst's estimate of earnings per share of the focal firm being less accurate than the consensus estimate of all the other analysts following the firm. When the analyst's overestimate was twice as large as the consensus overestimate (defined as the mean of all analyst estimates that were larger than the firm's actual earnings per share), it was coded as a 1, and was otherwise set to 0. We focused on such high errors because social salience has been known to lead to extreme evaluations rather than moderate evaluations (Fiske and Taylor, 1991). Another reason for dichotomizing the variable is that we used it to predict abandonment and wanted to examine the hypothesis that people abandon commitments when the negative consequences of their actions become overwhelming (Staw and Ross, 1987). We also show a model of continuous errors as a robustness check. In computing these variables, we used the last available forecast by the focal analyst and the last available consensus forecast in the focal year.

We computed two independent variables to test our predictions on the effect of social proof on errors. *Recent adoptions at time of adoption* was measured as the natural logarithm of the number of analysts initiating coverage at the time the focal analyst first initiated coverage of the focal NASDAQ firm. *Recent adoptions weighted by status at time of adoption* was measured as the natural logarithm of the number of analysts weighted by status initiating coverage at the time the focal analyst first initiated coverage of the focal NASDAQ firm. Both of these variables were included as time-constant variables in the models predicting overestimation.

We used several control variables in the analyses of errors. Because some analysts may have been assigned coverage to replace a prior analyst employed at the same brokerage firm, we created an indicator variable called *replacement,* set to 1 in such cases, and 0 otherwise. We also included market value, market returns, institutional ownership, analysts following the industry, market makers, log of the total number of analysts following the firm, logged status of total analysts covering the firm, recent adoptions, recent adoptions weighted by status, recent abandonments, and recent abandonments weighted by status as controls in our analyses. Since the consensus estimate is more reliable when the number of analysts covering a firm is high, we expected the logged number of analysts following the firm to have a positive relation to the probability of overestimation relative to the consensus. All of these controls were lagged by a year.

The indicator variable for large overestimates suggested a choice analysis such as the logit, but we modified this approach to control for variations in the precision of estimates by an analyst covering a given firm. We did this by specifying random effects for analyst-firm dyads, which we estimated by the xtlogit procedure of Stata. The model is:

$$y_{it}^* = \mathbf{x}_{it}\,\beta + u_i + \varepsilon_{it}$$

$$y_{it} = 1 \text{ if } y_{it}^* > 0, \text{ and } 0 \text{ otherwise}$$

where u_i are realizations of independent draws from a normal distribution with zero mean and standard error σ_u. Specifying analyst-firm dyad effects should mitigate the possibility that the results are influenced by autocorrelation of errors within an analyst-firm dyad.

Abandonments. The universe of potential abandoners includes all analysts covering a focal firm. Thus, our unit of observation for abandonments was the analyst–NASDAQ-firm dyad, and we analyzed the rate at which analysts dropped coverage of the firm. Because it is possible that abandonments of coverage by analysts could be the result of intra-brokerage firm transfers of responsibility for a given stock, we also used the brokerage-firm–focal-NASDAQ-firm dyad as the unit of analysis to provide robustness checks. An abandonment event was defined as an analyst stopping the issuing of an earnings estimate and recommendations for the focal NASDAQ firm. The IBES database flags these terminations of coverage for each firm. We split the spells annually to update covariates. We computed the following independent variables to test our predictions about abandonments: *recent adoptions at time of adoption, recent adoptions weighted by status at time of adoption,* and *overestimation error* were measured as in the analysis of overestimation errors. *Recent abandonments* were measured as the natural logarithm of the number of analysts stopping coverage in the previous year, and *recent abandonments by high-status actors* were measured using the same weights as for adoptions. These variables were lagged by a year.

We used several control variables in the analyses of overestimation. We also included market value, market returns, institutional ownership, analysts following the industry, market makers, log of the total number of analysts following the firm, log of the status of the total number of analysts covering the firm, recent adoptions, recent adoptions weighted by status, recent abandonments, and status-weighted recent abandonments as controls in our analyses. All of these controls were lagged by a year. Table 2 displays the descriptive statistics for the data used to analyze drops. Most correlations among independent variables range from small to moderate. The data used to analyze overestimates are the same as these data except that the first year of coverage was also used. The descriptive statistics are similar, so we show only the statistics for the drop-coverage data.

The analysis of abandonments was conducted as a hazard rate analysis, but we followed the preferences of our Stata software in using a failure-time metric. Hazard rate and failure-time metrics are mathematically equivalent, but the coefficients of a failure-time specification are read as effects on the duration until failure (dropping the firm), so a positive coefficient means longer duration and thus lower hazard rate. We restricted our attention to firms added during our observation window, since the number of adds at the time of addition are only known for these. Accordingly, there is no left censoring in the sample. We used a split-spell specification in which each analyst-firm combination was considered a single subject, and standard errors were computed using the robust option, with clustering at the analyst-firm level. This gives better estimates of the standard errors than the default approach of assuming independence among the observations that constitute a single spell.

We conducted the selection of the parametric specification in two steps. The first analysis used the log-logistic function, which can be monotonic or nonmonotonic depending on the shape parameter, and used all independent variables except the lagged adoptions at the time of adopting. These covariates require omitting the first year of coverage, which would complicate the task of estimating the functional form of the hazard rate. The models showed a nonmonotonic shape, so in the next step the log-logistic function was compared with the log-normal, which is the other leading nonmonotonic function. The results were similar, but the log-normal had a better fit and was chosen for the final analysis. Its survivor function is:

Table 2

Descriptive Statistics and Correlation Coefficients for Earnings Overestimation and Abandonment of Coverage

Variable	Mean	S. D.	1	2	3	4	5	6	7
1. Overestimate	0.211	0.407							
2. Abandonment	0.374	0.483	.11						
3. Market value	780.62	1702.27	.03	–.04					
4. Market returns	0.058	0.517	–.03	–.07	.06				
5. Variance returns	0.094	0.110	.00	.07	–.13	–.06			
6. Institutional ownership	40.57	21.05	.00	–.05	.20	.13	–.17		
7. Analyst covering industry	1869	1409	.01	–.03	.06	.00	–.09	.01	
8. Market makers	19.800	11.505	.05	–.03	.48	.01	–.02	.38	.10
9. Log analyst coverage	2.184	0.729	.04	–.07	.46	–.03	–.23	.45	.13
10. Log coverage weighted by status	1.077	1.083	.03	–.03	.29	.04	–.10	.25	.09
11. Log adoptions	1.090	0.641	.02	–.01	.21	.07	–.12	.22	.01
12. Log adoptions weighted by status	0.561	0.851	.01	–.01	–.01	.04	–.03	.09	.01
13. Log abandonment	0.625	0.609	.02	.00	.09	–.09	.02	.21	–.08
14. Log abandonment weighted by status	0.632	0.939	.01	–.02	.16	–.02	–.02	.19	.06
15. Replacement add	0.087	0.282	.07	.04	.02	.00	–.03	.00	.05
16. Log adds when adopted	1.206	0.627	.03	–.00	.21	.03	–.07	.21	–.02
17. Log adds when adopted, weighted by status	0.674	0.910	.03	.00	.09	–.01	–.00	.11	–.01
18. Lag overestimate	0.142	0.349	.09	.01	.03	–.03	–.02	–.01	.02

Variable	8	9	10	11	12	13	14	15	16	17
9. Log analyst coverage	.73									
10. Log coverage weighted by status	.45	.55								
11. Log adoptions	.37	.49	.51							
12. Log adoptions weighted by status	.12	.22	.67	.53						
13. Log abandonment	.37	.43	.29	.27	.18					
14. Log abandonment weighted by status	.33	.40	.44	.35	.38	.22				
15. Replacement add	.01	.03	.03	.04	.00	–.01	.01			
16. Log adds when adopted	.39	.49	.37	.57	.32	.29	.27	.02		
17. Log adds when adopted, weighted by status	.27	.34	.36	.28	.27	.21	.33	.03	.25	
18. Lag overestimate	.04	.06	.02	.01	.00	.03	.03	–.01	.02	.04

$$S(t) = 1 - \Phi\left\{\frac{1n(t) - \mu}{\sigma}\right\}$$

where $\mu = x_{it}\beta$ is a linear combination of covariates with associated parameters to be estimated. We also compared the results of the full specification (which omits the first year) and the exploratory specification (all years included) and found that the covariates shared by the two specifications had consistent results.

RESULTS

Table 3 displays the results of our analyses of addition of coverage. Model 1 provides partial likelihood regression esti-

Table 3

Proportional Hazard Models of Adoption of Coverage*

Variable	Model 1 Added coverage by analyst	Model 2 Added coverage by brokerage
Average market value	–0.000018•	–0.000018
	(0.000010)	(0.000012)
Market-adjusted returns	0.057••••	0.037•••
	(0.014)	(0.013)
Variance in returns	–0.116••••	–0.093••••
	(0.014)	(0.015)
Institutional ownership	0.0018••••	0.0013•••
	(0.0005)	(0.0004)
Analysts covering industry	0.00006••••	0.00003••••
	(0.0001)	(0.0001)
Market makers for firm	0.0037••••	0.0034••••
	(0.0010)	(0.0010)
Selectivity instrument (λ)	0.087	0.043
	(0.084)	(0.086)
Logged analyst coverage	0.466••••	0.216••••
	(0.022)	(0.022)
Logged analyst coverage weighted by status	0.031•••	0.010
	(0.011)	(0.012)
Logged recent adoptions	1.088••••	1.480••••
	(0.023)	(0.023)
Logged recent adoptions weighted by status	–0.008	–0.028••
	(0.013)	(0.013)
Logged recent abandonments	0.030•	–0.004
	(0.018)	(0.017)
Logged recent abandonments weighted by status	0.001	0.009
	(0.010)	(0.010)
Log likelihood	–114,143.40	–75,663.22
Chi square, beta of covariates all zero (13 d.f.)	10,823.79••••	9,677.53••••
Number of observations	27,861	27,473

•$p < .10$; ••$p < .05$; •••$p < .01$; ••••$p < .001$; two-tailed tests.

*Robust standard errors adjusted for clustering are used for significance testing and reported in parentheses below the coefficient estimate. Model 2 treats analyst additions of a firm already covered by the brokerage as a censoring event. It omits observations where two analysts from the same brokerage followed a firm concurrently.

mates of the rate of coverage initiations per firm. The number of recent adoptions significantly increases adoptions, consistent with H1, but the status-weighted number of adoptions does not give an additional effect. The results provide clear evidence of social proof through the actions of recent adopters but suggest that high-status analysts are not more influential than others. The number of recent abandonments has no significant effect on adoptions. The rate of coverage addition is increased by stock returns relative to market, institutional ownership, analyst coverage of industry and focal firm, and market makers. It is decreased by the variance of returns. Model 2 shows the rate of new coverage (adoptions that are not replacements) and shows similar results, except that the coefficient of recent adoptions is now numerically much greater, and the status of recent adopters has an unexpected negative effect. This effect is one-28th of the main effect of recent adoptions and means that adoptions by high-status analysts increase the rate of adoption but have a weaker effect than adoptions by low-status analysts. The coefficients of the control variables change little, but a comparison of the coefficient of the level of coverage shows that firms with a high level of coverage will have many replacement additions but also get some new additions.

Table 4 shows the results of the analyses of forecast errors. Model 3 examines the most reputation-threatening form of forecast error: large overestimates of firm earnings. This analysis had an indicator dependent variable set to one if the analyst overestimation error was more than twice the average overestimation error across all analysts covering the firm. Thus, this variable captures situations in which an analyst has made an overestimate of the firm's earnings that is high compared with those of other analysts. Consistent with H2, recent adoptions and recent adoptions weighted by the sta-

Table 4

Analysis of Earnings Overestimation*

Variable	Model 3 Random effects logit model of overestimation error	Model 4 Logit model of initial overestimation error	Model 5 Random effects logit model of later overestimation error	Model 6 Random effects tobit model of scaled overestimate	Model 7 Random effects model of prop. mean absolute forecast error
Intercept	−1.778••••	−1.632••••	−1.698••••	−1.433••••	1.028••••
	(0.075)	(0.091)	(0.112)	(0.220)	(0.142)
Average market value	−0.00000004•••	0.00000001	−0.00000005••••	−0.000000013••••	−0.00000001
	(0.00000001)	(0.00000002)	(0.00000001)	(0.000000003)	(0.00000002)
Market-adjusted returns	−0.247••••	−0.154•••	−0.306••••	−1.162••••	−0.156•••
	(0.036)	(0.049)	(0.050)	(0.102)	(0.058)
Variance in returns	−0.116••••	−0.106•••	−0.133••••	−0.032	−0.051
	(0.025)	(0.034)	(0.034)	(0.055)	(0.035)
Institutional ownership	−0.0035••••	−0.0038•••	−0.0036•••	−0.0089•••	−0.0035•
	(0.0009)	(0.0013)	(0.0012)	(0.0030)	(0.0020)
Analysts covering industry	−0.00002•	−0.00002	−0.00003†	−0.00021••••	−0.00003
	(0.0001)	(0.00002)	(0.00002)	(0.00004)	(0.00003)
Market makers for firm	0.010••••	0.008••	0.011••••	0.028••••	0.0016
	(0.002)	(0.003)	(0.003)	(0.008)	(0.0048)
Logged analyst coverage	0.091••	0.097•	0.082	0.015	0.322••••
	(0.042)	(0.052)	(0.063)	(0.013)	(0.083)
Logged analyst coverage weighted by status	−0.069•••	−0.100•••	−0.044	−0.196••	−0.034
	(0.026)	(0.037)	(0.034)	(0.082)	(0.049)
Logged recent adoptions	0.042		−0.028	0.030	0.034
	(0.035)		(0.049)	(0.108)	(0.064)
Logged recent adoptions, weighted by status	0.043		0.033	0.292•••	−0.054
	(0.032)		(0.041)	(0.100)	(0.059)
Logged recent abandonments	−0.010	0.013	−0.021	0.036	0.055
	(0.031)	(0.046)	(0.041)	(0.098)	(0.059)
Logged recent abandonments weighted by status	−0.027	−0.010	−0.036	−0.123••	−0.139••••
	(0.020)	(0.027)	(0.027)	(0.062)	(0.036)
Replacement addition	0.836••	1.072•••		2.456•	0.416
	(0.422)	(0.394)		(1.440)	(0.943)
Logged number of adoptions at time of initiation of coverage	0.114••••	0.107••	0.140•••	−0.067	−0.007
	(0.034)	(0.042)	(0.051)	(0.109)	(0.071)
Logged status of adoptions at time of initiation of coverage	0.058••	0.149••••	0.046	0.162••	0.133•••
	(0.024)	(0.039)	(0.029)	(0.078)	(0.051)
Random effects error component	0.781		0.858	3.523	2.994
Rho	0.379		0.424	0.208	0.300
Log likelihood	−14,168.98	−6,211.73	−7,971.23	−58,263.77	
Chi square, beta of covariates all zero (15 d.f.)	187.51••••	88.24••••	116.75••••	226.74••••	75.05••••
Number of observations	29,004	12,884	16,120	29,004	29,004

•$p < .10$; ••$p < .05$; •••$p < .01$; ••••$p < .001$; two-tailed tests.
*Standard errors are reported in parentheses below the coefficient estimate.

tus at the time that the focal analyst added the firm have significant positive effects. Thus, the size of the cascade at the time of adoption affects the error later on, so we have shown persistent error as a result of social proof. Analyses using different levels of overestimation error (available from the authors) strengthen this impression: when very large errors (triple the consensus error) are considered, the effect of the cascade is even greater than in the displayed model. When small errors (equal to the consensus error) are included, the cascade no longer has a significant effect. The cascade thus affects large overestimates more than small ones. An interesting control-variable result is the effect of handing a firm over from one analyst to another within a brokerage firm. It turns out that such replacements have a propensity to make large errors, and their estimates thus are worse than the estimates of a new analyst at a brokerage that has not previously covered the firm.

The analysis reported in model 3 does not distinguish between the first (initial) estimate of the analyst and subsequent estimates of the analyst, but in model 4 we predict the initial overestimate by the focal analyst and still find that recent adoptions and recent adoptions weighted by status at the time that the focal analyst added the firm have a significant positive effect. Because this model only has the initial overestimate for each analyst, it uses a logit model rather than a random effects logit, and it omits the number of recent adoptions, since they are the same as the recent adoptions at the time of adoption. Model 5 analyzes overestimates after the first year, showing that the recent adoptions at the time of adopting the firm have significant positive effects, but recent adoptions weighted by status do not. Thus, adopting a firm in the wake of other analysts triggers a social proof effect that leads to overestimates both in the initial year and (if the analyst keeps the firm) subsequent years. Analysts appear committed to their initial, erroneous estimates.

One issue concerns whether our overestimation variable should be defined as a continuous variable instead of an indicator variable. To investigate this, we defined the dependent variable as the forecast overestimate of the focal analyst scaled by the absolute error for all analysts and logged this variable to reduce skew. We used a tobit model with robust standard errors clustered by analyst–NASDAQ-firm dyad, since the dependent variable is bounded at zero. Model 6 shows that recent adoptions at the time the focal analyst added the firm have insignificant effects, but status-weighted recent adoptions at the time the focal analyst initiated coverage has a significant positive effect. These results suggest that the effects of social proof are more easily discerned when focusing on large overestimates, as in model 3.

It could also be argued that we should analyze underestimates as well, which can be done by measuring the absolute forecast error. Clement (1999) calculated a proportionate mean absolute forecast error (PMAFE), defined as the analyst's absolute forecast error minus the average of all analysts' forecast errors, divided by the average of all analysts' forecast errors. This treats over- and underestimates equally, whereas our primary interest was in overestimates. Model 7 has the PMAFE as the dependent variable, and the results indicate that recent adoptions at the time the focal analyst added the firm have insignificant effects, but status-weighted recent adoptions at the time the focal analyst initiated coverage has a significant positive effect. When juxtaposed with the results of model 3, these results indicate that social proof leads to extreme overestimates rather than small overestimates. Adoptions by high-status actors at the time of adoption appear to cause worse estimates, according to all three of our outcome measures, however, suggesting that their effect on the analysts' judgment is rather strong.

Table 5 reports failure-time models of analysts' time to abandonment of coverage. Model 8 shows abandonments of coverage by analysts and treats the time from adding coverage to dropping coverage as the dependent variable. This is equivalent to a hazard rate model, and the coefficients can be interpreted similarly, except that the signs are reversed—a positive sign means longer time until dropping the firm. We find that the hazard rate initially rises and then declines, consistent with prior research on the duration dependence of relationships (Levinthal and Fichman, 1988; Brüderl, 2000). The status of recent coverage additions makes analysts keep the firm longer and so does current following. These results suggest a mimetic process, but a negative effect of the cascade at the time of adding the firm would prove that social proof causes regret. This is exactly what model 8 shows: both recent adoptions and recent status-weighted adoptions at the time of the focal analyst adding the firm cause the analyst to keep the firm for a shorter time, supporting H3. Also, forecast overestimates show a significant negative effect, consistent with the argument for H4 that regret leads to abandonment. Finally, we find no support for H5: neither recent abandonments nor recent abandonments by high-status actors had a statistically discernable effect on analysts' abandonments.

We also checked whether overestimation error at initiation of coverage leads to drops, and model 9 shows that it does, thereby indicating that accumulation of negative information soon after coverage leads to abandonment. Once again, there is support for H3 and H4. Because abandonments could be the result of an intra-brokerage-firm transfer of responsibilities, we reestimated model 8 using brokerage-firm–focal-NASDAQ-firm dyads as the unit of observation. Identical results would mean that similar processes operate even when analysts are shuffled in brokerage firms. Model 10 provides similar patterns of support for H3 and H4: more adopters and more high-status adopters at the time of initiation of coverage cause the analyst to cover the firm for a shorter duration. Also, recent adoptions have insignificant effects, but recent status-weighted adoptions at the time the brokerage firm initiated coverage significantly reduce the duration of coverage. Large errors also shorten coverage duration significantly, and the shape parameter is similar to that reported in model 8.

We also used different specifications of error and still found support for H4. Model 11 includes the forecast overestimate

Table 5

Log Normal Failure Time Models of Abandonment*

Variable	Model 8 Analyst abandonment	Model 9 Analyst abandonment	Model 10 Brokerage abandonment	Model 11 Analyst abandonment	Model 12 Analyst abandonment
Intercept	5.771••••	5.782••••	5.734••••	5.808••••	5.765••••
	(0.096)	(0.096)	(0.105)	(0.096)	(0.096)
Average market value	0.00000003•	0.00000003•	0.00000002	0.00000002•	0.00000003•
	(0.00000001)	(0.00000001)	(0.00000002)	(0.00000001)	(0.00000001)
Market-adjusted returns	0.283••••	0.282••••	0.247••••	0.269••••	0.284••••
	(0.038)	(0.038)	(0.040)	(0.038)	(0.038)
Variance in returns	–0.085••••	–0.084••••	–0.075•••	–0.082•••	–0.084••••
	(0.024)	(0.024)	(0.024)	(0.024)	(0.023)
Institutional ownership	0.0013	0.0013	0.0019†	0.001	0.001
	(0.0010)	(0.0010)	(0.0011)	(0.001)	(0.004)
Analysts covering industry	0.00003	0.00002	0.00002	0.00002	0.00003
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Market makers for firm	–0.008•••	–0.007•••	–0.010•••	–0.007•••	–0.008•••
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log analyst coverage	0.285••••	0.285••••	0.227••••	0.282••••	0.284••••
	(0.056)	(0.056)	(0.059)	(0.053)	(0.056)
Log analyst coverage weighted by top-10 mentions	–0.010	–0.011	–0.040	–0.010	–0.010
	(0.030)	(0.030)	(0.033)	(0.030)	(0.030)
Logged recent adoptions	0.028	0.028	0.066	0.024	0.026
	(0.053)	(0.053)	(0.057)	(0.053)	(0.053)
Logged recent adoptions, weighted by top-10 mentions	0.087••	0.087••	0.106•••	0.089••	0.088••
	(0.036)	(0.036)	(0.041)	(0.036)	(0.036)
Logged recent abandonments	–0.053	–0.054	–0.020	–0.049	–0.053
	(0.037)	(0.037)	(0.041)	(0.037)	(0.037)
Logged recent abandonments weighted by top-10 mentions	0.023	0.022	0.022	0.022	0.023
	(0.022)	(0.022)	(0.023)	(0.022)	(0.022)
Logged number of adoptions at time of initiation of coverage	–0.125•••	–0.124•••	–0.082•	–0.127•••	–0.126•••
	(0.043)	(0.042)	(0.047)	(0.023)	(0.043)
Logged status of adoption at time of initiation of coverage	–0.087••••	–0.086••••	–0.084••••	–0.087••••	–0.088••••
	(0.023)	(0.023)	(0.025)	(0.023)	(0.023)
Overestimation error	–0.144•••	–0.072	–0.151•••		
	(0.051)	(0.061)	(0.055)		
Overestimation error at time of initiation of coverage		–0.124••			
		(0.056)			
Scaled overestimate error				–0.114••••	
				(0.032)	
Proportional mean absolute forecast error					–0.009••
					(0.004)
Log normal shape parameter	1.201••••	1.199••••	1.115••••	1.200••••	1.200••••
	(0.022)	(0.022)	(0.021)	(0.018)	(0.021)
Log likelihood	–10,273.92	–10,271.20	–7,879.75	–10,270.28	10,275.94
Chi square, beta of covariates all zero (15 d.f.)	187.60••••	193.83••••	140.00••••	187.01••••	180.14••••
Observations	19,038	19,038	18,233	19,038	19,038

•$p < .10$; ••$p < .05$; •••$p < .01$; ••••$p < .001$; two-tailed tests.
*Standard errors are reported in parentheses below the coefficient estimate. These are robust and adjusted for clustering on analyst.

of the focal analyst scaled by the absolute error for all analysts, and it significantly increases abandonments. Model 12 uses the proportionate mean absolute forecast error, and it also significantly enhances abandonments.

The results did not support H5. Recent abandonments and recent abandonments weighted by status did not significantly increase abandonments in any of our analyses. One reason for the insignificant effects may be that abandonments generate cognitive dissonance for analysts, but analysts may find such dissonant information based on the actions of others easier to ignore than dissonance stemming from their own overestimates. Thus, social proof may be more potent during adoption than abandonment because analysts can overlook dissonance created by the abandonment actions of their peers. It is also possible that the effect of abandonments was reduced because some firms experienced both abandonments and additions at the same time. Inconsistency in social proof makes it easier for actors to remain committed to their previous decision.

DISCUSSION AND CONCLUSION

The heuristic of social proof, like other cognitive shortcuts, reduces search costs but also produces errors (Cialdini, 1993). Neoinstitutional researchers have documented the ubiquity of imitation in adoption decisions, but they have paid little attention to how reliance on social proof can produce postdecision regret and induce decision makers to abandon a course of action. We extend the neoinstitutional approach by showing the full cycle of adoption, evaluation, and (sometimes) abandonment.

The findings lend support to the thesis that the heuristic of social proof underlies adoption decisions but also leads to postdecision regret that induces decision makers to reverse course. The research departments of investment banks and brokerage houses were more likely to adopt a focal firm for coverage when peers had recently adopted it. Yet analysts that adopted in the wake of an information cascade were more likely to be overly optimistic about the firm's earnings prospects, to become disappointed, and subsequently to abandon coverage. Social proof is a double-edged sword: it is easy for decision makers to use, but precisely because it is easy to use, it leads to errors and decision reversals. Thus, mimetic institutionalization effects are fragile. Moreover, in contrast to adoptions, we did not find information cascades for abandonment. Although this is contrary to our initial expectations, it is consistent with the basic argument of the cascade literature. Potential adopters rely on the actions of others to infer the value of a course of action because they are uncertain of its value. Once they have adopted and can make direct evaluations, they do not use external cues to make choices about abandonment.

The findings suggest that the application of institutional theory to the spread of a given behavior requires consideration of whether the true value of that behavior remains uncertain after the adoption. When values are observable after adoption, this significantly alters the institutionalization dynamic, allowing cycles of adoption, disappointment, and abandonment as we observed here. By contrast, values that are uncertain even after adoption can cause complete institutionalization, possibly followed by mimetic abandonment when a competing institution is introduced. The structure and behavior of educational organizations were an initial test case for institutional theory because educational outcomes are so difficult to evaluate that one often finds that education is understood to occur when certain institutions are present (Meyer and Rowan, 1978). Uncertainty may remain after adoption for complex strategic behaviors as well, but it is likely that changes to the core technologies of organizations can be evaluated after adoption. In that case, diffusion does not imply institutionalization, because abandonment caused by disappointment may follow.

These results also speak to the ongoing debate in neoinstitutional theory about agency. Some scholars contend that neoinstitutionalist accounts of adoption depict actors as cognitive dopes (Swidler, 1986; Oliver, 1991), and others suggest that actors are cognitive entrepreneurs (Scott, 1995). Our study shows that decision makers may rely on social proof to make adoption decisions, but after they experience postdecision regret, they reverse course. This clearly contradicts a conception of actors as cultural dopes, since abandonment implies that actors discover and correct mistakes. It also shows that agency need not be equated with institutional entrepreneurship; rational agents are prone to the same mimetic adoption behaviors as cultural dopes are. The difference between the two models becomes apparent when the post-adoption behavior is studied.

A related implication is that imitation is not necessarily a source of order. An implicit premise of neoinstitutional accounts is that imitation creates social order: eventually all potential adopters adopt because they are drawn by the pull of social proof (Miner and Raghavan, 1999). The underlying logic is that cognitive heuristics like social proof reduce uncertainty, but because cognitive heuristics can foster errors, imitation can be not only a precursor to order but can also sow the seeds of disorder. Decision makers beguiled into adopting a course of action may update their beliefs and abandon it. Since cognitive heuristics such as social proof provide the micro-foundations for neoinstitutionalism, researchers ought to be sensitive to their dual effects of reducing search costs and fostering errors.

Our results also add to the literature on postdecision regret. To date, postdecision regret has been explored in the context of auctions, where it is embodied in the idea of the winner's curse and decision makers face numerous alternatives exemplified in the idea of buyer's remorse (Bell, 1982; Loomes and Sugden, 1982; Harrison and March, 1984). Our study extends this line of work by suggesting that sequential decision making can be characterized by information cascades when actors use the heuristic of social proof and thereby overvalue a course of action and experience postdecision regret. Students of decision making treat postdecision regret as a special case of cognitive dissonance. Extant research is predominantly concerned with cognitive strategies to reduce postdecision dissonance, such as selective exposure, selective interpretation, and selective recall (Fiske and Taylor, 1991), but has devoted little attention to behavioral strategies. Cognitive strategies are deployed when the decision threatens the self-concept, is irrevocable, and there is public commitment. Behavioral change is feasible, however, when decisions are reversible and do not necessarily threaten the self-concept. Although the decision to adopt a focal firm entails some public commitment on the part of the research department, it is revocable, and abandonment does not jeopardize the image of the research department. Our study shows that behavioral change in the form of abandonment is feasible.

Some of our findings suggest that more work needs to be done to examine how adoption and abandonment processes influence each other. We found clear effects of recent adoptions on both adoptions and abandonment, as suggested by the theory, but the only effect of recent abandonments was a small increase in adoptions that appeared to be driven by replacement of analysts within the brokerage firm. One explanation might be that potential adopters ignore abandonments due to the cognitive bias of searching for confirmatory information (Higgins and Bargh, 1987), while analysts considering abandonment have sufficient knowledge of the value of the firm to make the abandonments by others uninformative. This interpretation raises the question of how much postdecision uncertainty should remain in order to produce a mimetic effect of abandonments. It is also interesting and unexpected that replacement adoptions were followed by strong overestimates. We favor the explanation that replacement adoptions were accompanied by exactly the wrong amount of knowledge transfer: enough to give the new analyst confidence to make bold estimates, but not enough to enable the new analyst to give accurate estimates. An alternative explanation would be that replacements occur when a high-status analyst senses that a firm's performance will deteriorate and unloads coverage on someone lower in the analyst pecking order.

The limitations of the study point to the need for future research. This study showed how information cascades promoted postdecision regret and led to abandonments when the decision was easily revocable. Future research is needed to explore how information cascades lead to postdecision regret when decisions are costly to revoke. For example, social proof can create bubbles in credit markets (e.g., bank and credit card loans) and in asset markets, such as real estate and construction. The decisions contained in such bubbles can be costly to reverse, creating much poorer conditions for reacting to postdecision regret by behavioral change. Another possibility is to study how the use of social proof is tied to the incentives of decision makers. Do younger decision makers rely on social proof because they seek to avoid career risk (Hong, Kubik and Solomon, 2000)? Alternatively, are older decision makers more likely to rely on social proof because they have more to lose (Taylor and Clement, 1999)? Research is also needed on the use of social proof as a deception tactic. For example, in "pump and dump" schemes, stock promoters collaborate with company insiders to pay writers of online investment newsletters to make favorable statements about the company, misleading prospective investors, who assume that the investment letters are unbiased. Finally, research is needed on how decision makers can use information on the outcomes of the adoption decisions of others to correct the tendency for social proof to mislead. More research on social proof and postdecision regret is needed to understand what fans and arrests the diffusion of inefficient innovations.

Our study of the adoption and abandonment of firms by securities analysts suggests that the cognitive processes underlying institutionalization are subtler than prior work credits. Imitation in the face of uncertainty may be a "standard response," as DiMaggio and Powell (1983) pointed out—even highly-paid professionals with expansive access to information and strong incentives to make wise choices do it—but not all practices or structures that are imitated become institutions. Our results suggest that relying on social proof to infer the value of an action often leads to disappointment, regret, and rejection when the action did not live up to the adopter's heightened expectations. This dynamic implies a brake on processes of institutionalization: while many practices may experience a brief prevalence, relatively few are likely to go on to lasting prominence.

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