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Underreactions, overreactions and moderated confidence☆

Robert Bloomfield*, Robert Libby, Mark W. Nelson

Johnson Graduate School of Management, Cornell University, Ithaca, NY 14853-6201, USA

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Abstract

This paper presents a model in which a representative investor has only a noisy signal of the reliability of his information. This noise causes prices to underreact to reliable information and overreact to unreliable information. We call this phenomenon 'moderated confidence', because in both cases, the investor's confidence is moderated toward his prior expectation of reliability. Although moderated confidence can be consistent with rationality, we construct a laboratory setting in which it is not. Still, we find strong support for both types of price errors. We also find that tests of weak-form efficiency can indicate overreactions, even when tests of semi-strong-form efficiency indicate underreactions using exactly the same data. These results can help empirical researchers develop specific alternative hypotheses to market efficiency, by helping them predict ex ante whether a given research study is likely to reveal over- or underreactions. © 2000 Elsevier Science B.V. All rights reserved.

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* Corresponding author. Tel.: + 1-607-255-9407.

E-mail address: rjb9@cornell.edu (R. Bloomfield).

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1. Introduction

Empirical studies suggest that financial markets overreact to information in some cases, but underreact in others.[1] Taken separately, either type of anomaly could present a significant challenge to market efficiency. However, as Fama (1998) notes, improving on the efficient markets hypothesis requires the ability to predict when one type of anomaly should arise instead of the other. This paper takes a step in that direction by demonstrating that whether prices in laboratory financial markets appear to overreact or underreact to information depends on the reliability of investors' information.

We motivate our experiments with a model in which a representative Bayesian investor has only a noisy signal of the reliability of his information. Because the investor has imperfect information about signal reliability, the investor will overestimate the reliability of highly unreliable information and underestimate the reliability of highly reliable information, just as shown in the individual decision-making experiments of Griffin and Tversky (1992). We refer to this phenomenon as 'moderated confidence', because investors' confidence is always moderated toward an average level that is insufficiently extreme.

As a result of moderated confidence, a researcher can identify price biases by forming a portfolio based on the realization of the informative signal. The researcher will find a systematic underreaction if that signal is a relatively reliable one (such as a recent earnings announcement), and will find a systematic overreaction if that signal is a relatively unreliable one (such as a long-term earnings pattern). More generally, the more reliable the signal used to form the portfolio, the larger the observed underreaction or the smaller the observed overreaction.

The model shows that underreactions and overreactions can be consistent with rational Bayesian behavior. If investors truly learn about the reliability of their information with error, moderated confidence can be rational. However, if this error arises because investors attend to irrelevant cues to assess information reliability (as argued by Griffin and Tversky (1992)), then moderated confidence is not rational.

[1] The market is said to underreact to information if the market price does not move upward far enough in response to good news or does not move downward far enough in response to bad news. The market is said to overreact to information if the market price moves upward too far in response to good news or moves downward too far in response to bad news. Evidence of underreactions includes post-earnings-announcement drift (Bernard and Thomas, 1989, 1990) and the success of 'momentum' trading strategies (Jegadeesh and Titman, 1993; Chan et al., 1996). Evidence of overreactions includes long-term negative serial correlations in prices (De Bondt and Thaler, 1985, 1987) and overly extreme responses to sales growth (Lakonishok et al., 1994). See Daniel et al. (1998a, b) and Fama (1998) for more complete reviews of this literature.

Regardless of the rationality of moderated confidence, the model predicts that market prices will underreact more (or overreact less) to more-reliable information. In this paper, we test these predictions with two experiments. In both experiments, we provide investors with perfect information on the reliability of their information. Nevertheless, we anticipate that investors will exhibit moderated confidence.

In experiment 1, securities' values are determined by a coin-flipping exercise adapted from Griffin and Tversky (1992). To test for moderated confidence, we manipulate information reliability by manipulating the sample size of the coin flips that investors see. We measure market price errors by comparing a portfolio's market closing price with the expected value of the security being traded, given all of the information available to the market. We then test for pricing anomalies.

Our first experiment compares price errors in markets in which all investors have highly reliable information with price errors in markets in which all investors have highly unreliable information. Consistent with moderated confidence, the markets underreact more to more-reliable information than they do to less-reliable information.

Our second experiment examines whether moderated confidence persists with more experienced traders who simultaneously hold a more-reliable and a less-reliable signal. Holding two different signals at the same time should highlight the difference in their reliability levels, making it easier for subjects to respond appropriately. Experience might also be expected to reduce any price biases. However, our results are similar: prices underreact to more-reliable information and overreact to less-reliable information, consistent with moderated confidence.

Our second study also shows that the portfolio-formation rule can dramatically alter researchers' interpretation of anomalies. In addition to the above results, we find strong evidence that high prices are too high and low prices are too low. This violation of weak-form efficiency is analogous to the overreaction observed by De Bondt and Thaler (1985, 1987) and others. However, it would be misleading to suggest that our investors are overreacting to *information*, because we find large underreactions to more-reliable information and only slight overreaction to unreliable information (violations of semi-strong-form efficiency). The two tests yield different results because underreactions to reliable information in the presence of unreliable information often lead prices to move in the wrong direction. These movements appear as overreactions in weak-form tests, because high prices are too high and low prices are too low.

Overall, the study has a number of implications for empirical research. Evidence of moderated confidence suggests that markets should underreact more to events that provide more reliable information. Extant event studies may show a preponderance of underreactions simply because researchers prefer to focus on reactions to relatively informative events, such as earnings announcements, dividend announcements and analyst recommendations. The study also shows that a single type of error can reveal underreactions in semi-strong-form efficiency tests while revealing overreactions in weak-form efficiency tests. Thus, it may not be appropriate to conclude that empirical evidence of underreactions and overreactions somehow 'offset' one another (Fama, 1998).

Section 2 describes our theory and hypotheses. Sections 3 and 4 describe the experiments and their results. Section 5 explores how the experimental results can organize our understanding of extant empirical results and provide the basis for new empirical tests.

2. Theory and predictions

2.1. Information reliability

A number of recent models in behavioral finance assume that investors are overconfident in their responses to information, and use this assumption to predict both overreactions and underreactions to information. For example, Odean (1998), Gervais and Odean (1997), and Daniel et al. (1998a, b) apply overconfidence to rational expectations models, while Benos (1998), Kyle and Wang (1997), Odean (1998), Wang (1998) and Fischer and Verrecchia (1999) apply overconfidence to order-driven markets, following Kyle (1985). Barberis et al. (1998) consider a representative investor who behaves in a manner similar to that often described in the overconfidence literature.

The assumption of overconfidence is supported by decades of research establishing the tendency of individuals to believe they have more information or knowledge than they actually possess (see, e.g., Lichtenstein and Fischhoff, 1977; Lichtenstein et al., 1982). However, psychology research also produces evidence of underconfidence (see, e.g., Lichtenstein et al., 1982; Peterson and Pitz, 1986, 1988). In fact, the individual decision-making literature has struggled to predict when decision-makers will be over- and under-confident, just as the finance literature has struggled to predict when financial markets will over- and under-react.

Griffin and Tversky (1992) provide an explanation capable of predicting both under- and over-confidence in individual decision-making settings. They distinguish information according to two characteristics: strength and weight. In their terminology, the strength of evidence is the degree to which it appears favorable or unfavorable. The weight of evidence is its statistical reliability. Griffin and Tversky provide evidence that people tend to pay too much attention to strength and not enough attention to weight. As a result, overreactions should be observed when evidence is of high strength but low weight, and underreactions should be observed when evidence is of low strength but high weight.

2.2. A formal model of moderated confidence

We capture and generalize these reactions within the framework of Bayesian rationality by assuming that a representative investor has a prior belief regarding the reliability of available information, and then receives a noisy but unbiased signal of that reliability. Within the context of Griffin and Tversky's explanation, this noise arises because strength and weight are not perfectly correlated, and investors inappropriately attend to the former in assessing the latter. However, the noise could arise even with perfectly rational investors, if they simply lacked sufficient knowledge to assess information reliability perfectly.

For simplicity, we formalize these concepts in a model with a symmetric binary state space and symmetric binary variables. Formally, assume that the security value V is equal to either 0 or 1, with each value equally likely. A representative investor receives two signals. The first signal, $x \in \{0, 1\}$, takes on a value equal to V with probability $R > 0.5$, and takes on the other value with probability $1 - R$. The binary probability R represents the reliability of x, with higher values of R reflecting greater reliability.

The reliability of x is equal either to R_H or R_L, with each level of reliability equally likely. The second signal, $z \in \{R_H, R_L\}$, takes on a value equal to R with probability $\pi > 0.5$. Thus, z provides the investor with a noisy signal of the reliability of x.

The expected value of the security given the signal pair (x, z) is given by the following equation (which exploits the independence of z and x, conditional on R and V):

$$\mathrm{E}[V|(x,z)] = \Pr[V=1|(x,z)] = \Pr[V=1|x, R_H]\Pr[R_H|z] + \Pr[V=1|x, R_L]\Pr[R_L|z].$$

Fig. 1 illustrates the expected values for all four possible (x, z) pairs. An investor with good news ($x = 1$) will expect a value that is a weighted average of R_H and R_L, with greater weight on R_H if $z = R_H$, and greater weight on R_L if $z = R_L$. An investor with bad news ($x = 0$) will expect a value that is a weighted average of $(1 - R_H)$ and $(1 - R_L)$, with greater weight on $(1 - R_H)$ if $z = R_H$, and greater weight on $(1 - R_L)$ if $z = R_L$.

Because the investor's estimate is always Bayesian rational, these expectations are unbiased given (x, z). Thus, constructing portfolios on the basis of the investor's information–buying or selling whenever (x, z) takes on a particular realization–would yield a zero expected return. However, positive returns are possible when constructing portfolios on the basis of information about true reliability (R), because the investor does not have this information. For example, when the reliability is truly high ($R = R_H$), the investor underreacts to x, yielding a price that is too low when $x = 1$ and too high when $x = 0$. When reliability is

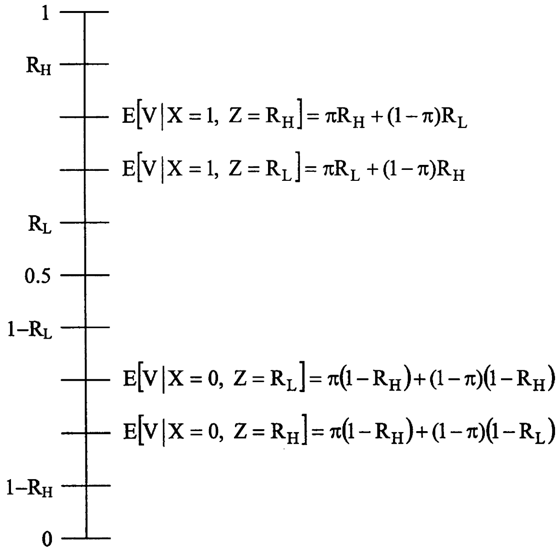

Fig. 1. This figure shows the expected value of a security given various sets of information. Value V is equal to either 1 or 0, with each value equally likely. A representative investor receives two signals. The first signal, $x \in \{0, 1\}$, takes on a value equal to V with probability $R > 0.5$, and takes on the other value with probability $1 - R$. The binary probability R represents the reliability of X, with higher values of R reflecting greater reliability. The reliability of x is equal either to R_H or R_L, with each level of reliability equally likely. The second signal, $z \in \{R_H, R_L\}$, takes on a value equal to R with probability $\pi > 0.5$. Thus, z provides the investor with a noisy signal of the reliability of x.

truly low ($R = R_L$), the investor overreacts to x, yielding a price that is too high when $x = 1$ and too low when $x = 0$.

Regardless of R and z, the investor's belief about reliability is moderated toward $(R_H + R_L)/2$, which is the investor's prior expectation of reliability. Thus, we refer to this phenomenon as 'moderated confidence'. Moderated confidence occurs in this setting because the investor's knowledge of reliability is only probable, not certain. As in any Bayesian model, this uncertainty leads the investor's posterior estimate of reliability to be a weighted average of the prior estimate, $(R_H + R_L)/2$, and the sample outcome, z. This basic intuition would extend readily to models with continuous probability distributions, although it can be difficult to characterize uncertainty about quantities (such as signal precision) that must be positive, because one cannot use the normal distribution.

Is moderated confidence rational? The answer depends on the reason for the investor's uncertainty about signal reliability. The uncertainty may simply reflect the impossibility of knowing the true reliability of the information at the time of the investor's decisions. For example, one might argue that post-earnings-announcement drift was not irrational in the first years in which the phenomenon was observed, because there was not yet sufficient evidence establishing that earnings surprises are a reliable indicator of future earnings changes. Although later studies have shown this predictive power, this does not mean that investors in the 1960s should have known it. However, given current knowledge about the reliability of past earnings changes for future earnings changes, it is hard to claim that post-earnings-announcement drift still reflects moderated confidence in a rational way.

Our model of moderated confidence can also be useful in predicting the behavior of irrational investors, as long as their irrationality appears *as if* they are rational investors with noisy signals about the reliability of their information. This would happen whenever investors' impressions of reliability are influenced by characteristics that are imperfectly correlated with true reliability, such as the information's strength or salience.[2] Thus, one could create a family of models that vary in the characterization of the imperfect correlation between perceived and actual reliability. If the investors are presumed to have more information about reliability than they actually use, then moderated confidence is not consistent with Bayesian rationality. The Bayesian model is still useful, however, because uncertainty regarding signal reliability still accurately reflects the types of errors that will arise: specifically, investors will underreact to data that are relatively reliable, and overreact to data that are relatively unreliable.

In this paper, we test these predictions with two experiments in which investors have perfect information on the reliability of their information. Thus, evidence of moderated confidence would suggest irrationality. Nevertheless, we anticipate support for the predictions of our Bayesian model. The next section describes our first experiment in detail.

3. Experiment 1

3.1. General terminology

In our laboratory markets, 'cohort' refers to a group of three investors who always trade together. A 'security' (a claim on a terminal dividend) is denominated in 'francs', a fictitious currency ultimately converted into cash. 'Trading round' refers to each time that all investors in a cohort enter orders to trade shares of a security. Trading is a batch process – all investors in a cohort

[2] If weight (reliability) and strength are negatively correlated (because it is rare to see an extreme sample proportion when drawing a very large sample), people may show biases more severe than in our model.

choose an action in each trading round, and the cohort moves together to the next round. 'Market' refers to a sequence of trading rounds for a single security. 'Session' refers to a three-hour laboratory trading session. All investors are MBA students at Cornell's Johnson Graduate School of Management.

3.2. Security values and information

The five securities used in our markets are closely modeled after five coin-flipping problems presented in 'study 1' of Griffin and Tversky's (1992) examination of individual decision-making biases. In our experiment, investors were told that we used computer simulations to characterize the following process. First, we generated a large equal number of two types of coins. 'Heads-biased' coins have a 60% chance of coming up heads when flipped, while 'tails-biased' coins have a 40% chance of doing so. We then flipped each coin some number of times, and placed it in a bucket with all of the coins that achieved the same result. Each bucket determines the value of a security; the value (in francs) is equal to the proportion of coins (in percent) in the bucket that are heads-biased. As an example, we told subjects that they might be presented with a bucket that contains all of those coins that came up with one head and one tail when flipped two times. Because such a large number of coins is simulated, Bayesian analysis reveals that 50% of the coins in the bucket should be heads-biased, so the value of the security would be 50 francs.

We presented each group of investors with the five different securities presented in Table 1. Three of the securities are based on the outcome of 17 coin flips; the other two are based on the outcome of three coin flips. 'Signal difference' refers to the absolute difference between the number of heads and the number of tails. 'Signal extremity' denotes the absolute difference between the proportion

Table 1
Securities used in experiment 1

Signal reliability (# of flips)	Signal difference (|#heads − #tails|)	Signal extremity[a]	Value extremity[b]
Low(3)	3 (3 − 0)	50.0	27
Low(3)	1 (2 − 1)	16.7	10
High (17)	5 (11 − 6)	14.7	38
High (17)	3 (10 − 7)	8.8	27
High (17)	1 (9 − 8)	2.9	10

[a] *Signal extremity* is the absolute difference between the proportion of heads observed and the prior expected proportion of 50%.

[b] *Value extremity* is the absolute difference between the security value and the prior expected value of 50 francs.

of heads observed and the prior expected proportion of 50%. 'Value extremity' indicates the absolute difference between the security value and the prior expected value of 50 francs. For example, 10 heads and 7 tails result in a signal difference of 3, a proportion of 58.8%, a signal extremity of 8.8, a security value of 77, and a value extremity of 27. Three heads and no tails result in a signal difference of 3, a proportion of 100%, a signal extremity of 50, a security value of 77, and a value extremity of 27.

3.3. Trading

As in Friedman and Ostroy (1995), Gillette et al. (1998), and Van Boening et al. (1993), investors trade securities in a clearinghouse market. The market is most similar to that used in Bloomfield and Wilks (2000). In each round of trading, each investor estimates the value of the security and chooses a linear demand schedule by choosing a reservation price and a slope. The reservation price is the price below (above) which the investor wishes to buy (sell) securities. The slope of the demand schedule determines how many shares the investor will buy (sell) for a price that is a given distance below (above) his reservation price. Trades are limited to 50 shares per investor per trading round.

Once all three investors have entered a demand schedule, a computer determines the market-clearing price at which supply equals demand. If there is a range of such prices, the computer chooses the midpoint of that range as the market-clearing price. Each investor then learns the market-clearing price, the number of shares that he or she traded at that price, the total trading volume, and his or her current balance in shares and cash.

Trading in each security lasts for four rounds. Investors start with 0 shares and 0 francs at the beginning of round 1. The first round of trade occurs before investors observe the coin flips; this allows an opportunity for risk sharing. Investors observe the coin flips before trading in round 2. Trading concludes after the fourth round of trade, at which point investors move to round 1 of the next security (if any). There are no restrictions on short selling or cash balances.

3.4. Experimental design

The experiment uses 9 cohorts of three investors each. Each cohort trades the same 5 securities shown in Table 1. To control for order effects, five of the cohorts trade with more-reliable information first, and the other four cohorts trade with less-reliable information first. The order in which various securities appeared within each reliability setting is also randomized between cohorts. Information of a given reliability and extremity is favorable about half the time (more heads than tails) and unfavorable about half the time (more tails than heads), and about half the securities traded by each cohort have favorable information, and the other half have unfavorable information.

3.5. Instructions

The instructions are shown in Appendix A. We begin by explaining the nature of trading in the clearinghouse market, without any discussion of the nature of the securities. Investors then trade two practice securities whose values are determined by the answers to 'general knowledge' questions. These securities allow subjects to gain experience with the trading mechanism, without influencing in any way their responses to the information for the later securities. Finally, we describe how security value was determined for the five securities used in the experiment.

3.6. Incentives

Subjects gain or lose francs by trading shares of each security. Gain or loss from trading each round is calculated by multiplying the number of shares a subject purchased by the difference between true security value and that round's current market price. Subjects who purchase (sell) securities earn francs if value is greater (less) than price, and lose francs if value is less (greater) than price. Gains from trading are not revealed until trading in all securities was completed, so as not to reveal the correct interpretation of the available information.

At the end of the experiment, the total number of francs gained or lost is multiplied by a 'conversion rate' of 1 cent per franc. We then add the resulting dollar amount to the promised average payment of $30 to determine the subject's payment (a minimum payment of $10 is guaranteed). To avoid risk-seeking behavior by investors who may be near or below the floor, we do not tell subjects either the floor or the conversion rate. We tell them only that average winnings will be approximately $30/session.

3.7. Results

Our analyses examine three different dependent variables. First, we examine errors in investors' estimates of value, because estimates allow us to tie our results most closely to prior studies in psychology (e.g., Griffin and Tversky, 1992) that use such measures almost exclusively. Estimates do not affect participants' winnings, so they should reflect only expectations of value, without being systematically influenced by risk preferences or other factors. Second, we examine the associated errors in reservation prices, which reflect investors' risk preferences and trading strategies, as well as their expectations of security value. Reservation prices also allow us to examine errors that arise even though they reduce participants' winnings. Third, we examine errors in market prices, which represent averages of investors' reservation prices, weighted by the slope of the investors' demand functions.

Simply testing for overreactions to less-reliable information and underreactions to more-reliable information would not provide a satisfactory test of moderated confidence, for two reasons. First, we cannot know in advance what levels of information reliability are sufficiently low to create overreactions or are sufficiently high to create underreactions. Second, there might be factors at work in both settings that lead investors to underreact or overreact to any signal, regardless of its reliability. We address both of these issues by testing for differences in errors across treatments, rather than simply testing for deviations from point predictions within treatments. Any treatment effect is readily attributed to information reliability, because all other factors are held constant or balanced across treatments.

Table 2 reports the results of experiment 1. To calculate errors in estimates, reservation prices and market prices, we calculate returns to a strategy

Table 2
Results of Experiment 1

Signal reliability	Signal difference (extremity)	Return to a contrarian strategy[a] using		
		Estimate as a proxy for market price	Reservation price as a proxy for market price	Final round market price
Low	3 (50.0)	3.70	− 1.81	− 2.88
Low	1 (16.7)	5.74	2.85	4.01
Mean low		4.72*	0.52	0.56
High	5 (14.7)	− 22.26***	− 26.37***	− 25.64***
High	3 (8.8)	− 15.81***	− 13.15***	− 13.69***
High	1 (2.9)	− 8.00***	− 5.70***	− 5.96***
Mean high		− 15.36***	− 15.07***	− 15.10***
Difference between low and high		20.08***	15.59***	15.66***

[a] *Returns to a contrarian strategy* measure the trading gains to a strategy of buying one share whenever the available signal is unfavorable and selling one share whenever the available signal is favorable. The table reports returns to this strategy under three different assumptions concerning the price at which transactions occur: average final-round estimate of value, average final-round reservation price, and closing final-round market price.

All p-values are the result of one-sided t tests.

*** $p < 0.01$.

* $p < 0.10$.

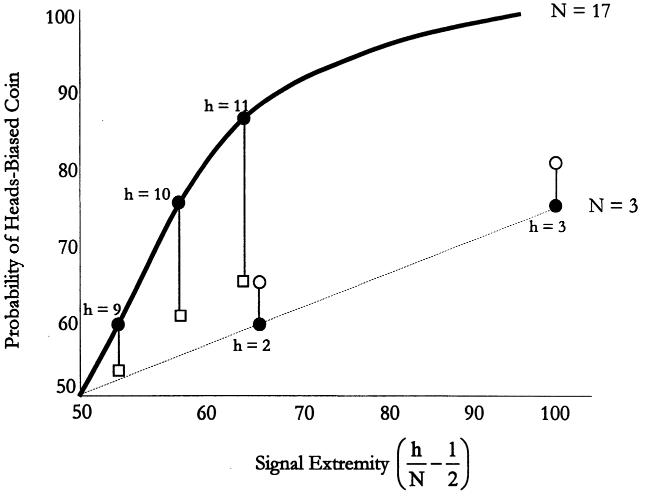

Fig. 2. Objective and estimated probabilities of a heads-biased coin as a function of signal extremity. Signal extremity is defined as the number of heads (h) divided by the total number of observed coin flips (N), less $\frac{1}{2}$. The solid dots indicate the probability of a heads-biased coin given signal extremities associated with particular outcomes of heads and tails. The curves reflect the same probability assuming fractional numbers of heads and tails, given 17 flips (bold line) and 3 flips (faint line). The hollow shapes indicate investors' estimates of the probability of a heads-biased coin when they observe 17 coin flips (squares) and 3 coin flips (circles).

of buying one share whenever the available signal is unfavorable and selling one share whenever the available signal is favorable. The table reports returns to this strategy under three different assumptions concerning the price at which transactions occur: investors' average final-round estimate of value (column 3), investors' average final-round reservation price (column 4), and the closing final-round market price (column 5). Positive returns indicate overreactions; negative returns indicate underreactions.

Fig. 2 presents the estimate results graphically. Consistent with moderated confidence, investors estimate a confidence level that is always less extreme than would be appropriate for the reliable and unreliable information. These results are consistent with Griffin and Tversky's (1992) work on individual decision making. Using the confidence ratings they report, we estimate that Griffin and Tversky would have measured returns of -15.5 (compared to -15.36 in our study) in the high-reliability setting and 5.5 (compared to 4.72 in our study) in the low-reliability setting.

To provide a more formal test of moderated confidence, we compute the mean difference in returns across the two reliability settings for each of the nine cohorts, and then perform a t-test on those nine differences. The returns to the contrarian strategy are significantly greater when investors have less-reliable information than when they have more-reliable information, regardless of the dependent measure used.[3] Analyses of variance provide similar results. Regardless of the dependent measure used, signal reliability is significant (supporting moderated confidence), signal difference is significant (indicating that underreactions and overreactions were more severe as the information was more extreme) and the reliability $\times$ difference interaction is insignificant.[4]

These results provide strong support for moderated confidence in investors' estimates, in investors' reservation prices, and in the market prices that result from investors' trades. Finding moderated confidence in estimates extends the prior work in psychology to our setting. Finding moderated confidence in reservation prices indicates that the biases apparent in estimates do not arise simply because estimates are not tied to investors' winnings; biases are also clearly evident when measured with reservation prices, which are tied to winnings. Finding moderated confidence in market prices indicates that 'smart traders' do not trade aggressively enough to drive market prices to a less-biased closing value.

We also examine the statistical significance of moderated confidence within each reliability setting. Regardless of which dependent variable we examine, we identify significant underreactions in the high-reliability setting. For example, with respect to estimates, the mean return over all 9 cohorts is -15.36 in the high-reliability setting, which is significantly less than zero ($t = -16.37$, $p = 0.0001$), indicating that investors' estimates underreact to the more-reliable information: when the information is favorable (unfavorable), estimates are not high (low) enough.

In contrast, we identify a significant overreaction in the low-reliability setting only with respect to individual estimates [with a mean return of 4.72 in the low-reliability setting ($t = 5.64$, $p = 0.0182$)]. Overreactions are not significantly different from zero with respect to reservation prices and market prices. Paired t-tests also indicate insignificant differences between returns when based on estimates, reservation prices and market prices.

Why are overreactions to less-reliable information less pronounced than underreactions to more-reliable information? Within the context of the

[3] For all analyses in both experiment 1 and experiment 2, medians are very similar to means, and all results are very similar when data are rank-transformed.

[4] Specifically, with respect to estimates, reliability is significant ($F = 61.31$, $p < 0.0001$), difference is significant ($F = 5.62$, $p < 0.0141$), and the reliability $\times$ difference interaction is insignificant ($F = 0.99$, $p < 0.3490$). With respect to reservation prices, reliability is significant ($F = 15.80$, $p < 0.0041$), difference is significant ($F = 8.45$, $p < 0.0031$), and the reliability $\times$ difference interaction is insignificant ($F = 0.26$, $p < 0.6255$). With respect to market prices, reliability is significant ($F = 10.45$, $p < 0.0068$), difference is significant ($F = 6.94$, $p < 0.0120$), and the reliability $\times$ difference interaction is insignificant ($F = 0.01$, $p < 0.9100$).

Bayesian model of moderated confidence, this asymmetry might arise because investors' prior beliefs are that their data will be relatively unreliable. Alternatively, floor and ceiling effects might contribute to the asymmetry. In particular, observed estimates probably reflect the investors' true estimates with error. This error cannot be completely symmetric, because observed estimates must be no less than 0 and no greater than 100. Thus, random error will systematically bias observed estimates toward 50, and will do so more as true estimates become more extreme.

Regardless, returns to the contrarian strategy are always significantly larger in the high-reliability setting than they are in the low-reliability setting. Thus, moderated confidence is supported for each dependent variable.

4. Experiment 2

Experiment 1 provided strong evidence that moderated confidence can affect market behavior, even in a setting in which moderated confidence is difficult to reconcile with rational behavior (because investors should have been able to determine perfectly the reliability of their information). In our next experiment, we change several aspects of the experiment to increase the likelihood that investors will be able to avoid biases. First, we use the same subjects who participated in experiment 1, so that the subjects have greater experience in experiment 2 than they had in experiment 1. Second, we provide subjects with *both* a highly reliable signal and a highly unreliable signal for each security. (All investors still receive the same information.) Because investors can compare the more- and less-reliable information directly, this within-markets manipulation should make the differences in information reliability more salient to investors, helping them to avoid any misweighting that would occur given a between-subjects manipulation (Kahneman and Tversky, 1996).

4.1. Method

At the end of experiment 1, we provide subjects an additional screen of instructions that explain the manner in which security values were determined in experiment 2 (see Appendix A). The only difference is that security value (in francs) in experiment 2 is equal to the average of the percentages of heads-biased coins in *two* buckets. For example, if one bucket has 30% heads-biased coins and the other has 50% heads-biased coins, then the average proportion is 40%, because (30% + 50%)/2 = 40%. The value of this security is 40 francs.

For each security, one bucket consists of coins that achieved a certain result after being flipped 17 times, while the other bucket consists of coins that achieved a certain result after being flipped three times. Thus, all investors have one relatively reliable signal (the outcome of the 17 flips in one bucket) and one relatively unreliable signal (the outcome of the 3 flips in the other bucket). All other aspects of the task are identical to experiment 1.

We present each group of investors with the six different securities shown in Table 3. The securities are formed by crossing 2 levels of the less-reliable (3-flip) signal with 3 levels of the more-reliable (17-flip) signal. The signal difference of the less-reliable signal takes on values of either 3 or 1. The signal difference of the more-reliable signal takes on values of 5, 3 or 1.

The less-reliable signal always has a sign opposite that of the more-reliable signal. We focus on securities with conflicting information because it allows us to test most powerfully whether the markets react differently to the two different signals. When both signals are of the same sign, an overreaction to one signal can counteract an underreaction to another. Thus, subjects could be over- (under-) reacting to the less- (more-) reliable signal, just as predicted by moderated confidence, but these effects could offset such that we could not observe them. On the other hand, if signals are of opposite signs, underreaction to one signal combines with overreaction to the other signal to create a single cumulative unidirectional effect that is relatively easier to detect.

Table 3
Securities used in experiment 2

Signal difference (extremity) of less-reliable signal	Value extremity indicated by less-reliable signal[a]	Signal difference (extremity) of more-reliable signal[b]	Value extremity indicated by more-reliable signal	Security value extremity[c]
3 (50.0)	27	5 (14.7)	38	5.5
3 (50.0)	27	3 (8.8)	27	0.0
3 (50.0)	27	1 (2.9)	10	8.5
1 (16.7)	10	5 (14.7)	38	14.0
1 (16.7)	10	3 (8.8)	27	8.5
1 (16.7)	10	1 (2.9)	10	0.0

[a] *Value extremity of the less-reliable signal* is the absolute value of the difference between 50 and the security value indicated by the proportion of heads in the less-reliable signal (3 flips), ignoring the value indicated by the more-reliable signal.

[b] *Value extremity of the more-reliable signal* is the absolute value of the difference between 50 and the security value indicated by the proportion of heads in the more-reliable signal (17 flips), ignoring the value indicated by the less-reliable signal.

[c] *Security value extremity* is the absolute distance of the security value from the prior expected value of 50 francs. The value of each security in experiment two is the average of the values indicated by the less- and more-reliable signals. For every security, the less- and more-reliable signals offset each other, because either the less-reliable signal is favorable and the more-reliable signal is unfavorable, or else the less-reliable signal is unfavorable and the more-reliable signal is favorable. So, security value extremity equals |(value extremity indicated by less-reliable signal) −(value extremity indicated by more-reliable signal)|. For example, the value extremity of the first security in the table is given by $(|27-38|)/2=5.5$.

To balance the design, approximately half of the securities seen by each cohort include a favorable less-reliable signal and an unfavorable more-reliable signal, while the remaining securities include an unfavorable less-reliable signal and a favorable more-reliable signal.

4.2. Results

For our initial analysis of the data from experiment 2, we compute the returns to portfolios that should yield positive returns if investors overreact to less-reliable information and underreact to more-reliable information (as predicted by moderated confidence). Recall that the more- and less-reliable information is always of opposite sign (one indicates a value above 50 while the other indicates a value below 50). These portfolios therefore involve (1) buying whenever the less-reliable signal is unfavorable and the more-reliable signal is favorable, and (2) selling whenever the less-reliable signal is favorable and the more-reliable signal is unfavorable.

Table 4 shows the return to this strategy is positive and statistically significant whether the transaction price is equal to investors' fourth-round average estimates (return $= 9.24$, $t = 7.82$, $p = 0.0001$), reservation prices (return $= 10.00$, $t = 7.87$, $p = 0.0001$) or market prices (return $= 8.72$, $t = 4.77$, $p = 0.0007$). For all measures, the return is statistically significant for at least five of the six securities at the $p < 0.10$ level. These results are similar whether we use estimates, reservation prices or market prices to compute returns. Thus, the data from experiment 2 provide strong support for moderated confidence.

Because the more- and less-reliable signals always have opposite signs, it is difficult for us to determine how much of the return arises from underreactions to more-reliable information, and how much arises from overreactions to less-reliable information. It is likely that most of the returns are underreactions to more-reliable information, because these were much larger in experiment 1 than were the overreactions to less-reliable information. An analysis of variance in experiment 2 reveals a similar result. Using market price to compute returns, we find that changes in the more-reliable signal significantly influence portfolio returns ($F = 5.00$, $p = 0.0205$), but changes in the less-reliable signal do not ($F = 0.19$, $p < 0.6707$). The interaction between the signals is also insignificant ($F = 0.04$, $p = 0.9644$). Results using estimate or reservation prices as a proxy for price are very similar. Thus, the pattern of results is quite similar to those in experiment 1.

Overall, these analysis suggest that, as in experiment 1, the markets strongly underreact to more-reliable information, but overreact only slightly, if at all, to less-reliable information. More generally, results of experiment 2 again support moderated confidence, even though investors' greater level of experience and the within-subjects manipulation of signal reliability should both help investors avoid unintended misweighting of information.

Table 4
Results of experiment 2

Signal difference (extremity) of less-reliable signal	Signal difference (extremity) of more-reliable signal	Return to a contrarian strategy using:[a]		
		Estimate as a proxy for market price	Reservation price as a proxy for market price	Final round market price
3 (50.0)	5 (14.7)	15.28***	11.91***	11.30**
3 (50.0)	3 (8.8)	12.15***	10.30***	9.25**
3 (50.0)	1 (2.9)	5.35*	4.57*	2.75
1 (16.7)	5 (14.7)	10.07***	15.63***	14.61***
1 (16.7)	3 (8.8)	8.57***	12.13***	10.05*
1 (16.7)	1 (2.9)	4.04***	5.44***	4.34***
Mean		9.24***	10.00***	8.74***

[a] *Returns to a contrarian strategy* measure the trading gains to a strategy of buying one share whenever the less-reliable signal is unfavorable and selling one share whenever the less-reliable signal is favorable. (Given that the less-reliable and more-reliable signals always have opposite signs, this strategy is equivalent to that of buying one share whenever the more-reliable signal is favorable and selling one share whenever the more-reliable signal is unfavorable.) The table reports returns to this strategy under three different assumptions concerning the price at which transactions occur: average final-round estimate of value, average final-round reservation price, and closing final-round market price.

All p-values are the result of one-sided t tests.

***$p < 0.01$
**$p < 0.05$
*$p < 0.10$

4.3. Tests of weak-form efficiency

All of our tests to this point have been tests of semi-strong-form efficiency: we form portfolios based on the information presented to investors. We now examine weak-form efficiency by forming contrarian portfolios that involve selling whenever prices rise above 50 francs, and buying whenever prices fall below 50 francs. This analysis is similar to that used in De Bondt and Thaler (1985, 1987). Overall, returns to this strategy are 10.34 ($t = 4.29$, $p < 0.001$), indicating that high prices are too high, and low prices are too low. The return to this contrarian strategy is significantly positive (at $p < 0.001$) for five of the six securities. Thus, this analysis suggests strong overreactions to information.

This result may seem inconsistent with our claim that our markets underreact to reliable information. We believe that the inconsistency arises because the underreactions to the more-reliable information often cause prices to rise when they should fall, and vice versa. For example, assume that, as in line 1 of Table 4, investors observe 0 heads out of 3 flips (signal difference = 3), and 11 heads out of 17 flips (signal difference = 5). In this case, the security value should be 55.5, because the unreliable bad news is outweighed by the reliable good news. However, closing market prices average 44.2 (yielding a price error of 11.30). Although the price error could arise entirely from an underreaction to the reliable information, a weak-form test shows an unambiguous overreaction: the low price is much too low.[5]

Weak-form overreactions are exacerbated by the relatively central values of our securities. If the security has a value of 50, any price other than 50 appears as a weak-form overreaction. Evidence of weak-form overreactions might be slightly less strong if we included securities for which both the reliable and unreliable signals were favorable (or both were unfavorable). However, such securities would probably yield roughly equal over- and underreactions in weak form tests, and so would be unlikely to eliminate an overall tendency toward weak-form overreactions.

Overall, this analysis shows that weak-form efficiency tests can lead to conclusions that are very different from those drawn from semi-strong-form efficiency tests. We believe that it would be inappropriate to conclude that investors in experiment 2 overreact strongly to their information. Because weak-form tests form portfolios on the basis of price, rather than information, they can be subject to a variety of extraneous factors. For example, if price reflects investors' value estimates with random error, that error can induce weak-form overreactions if high prices tend to include positive random error, while low prices tend to include negative random error. Thus, we believe that the most accurate way to assess information-related biases is through event study methods that condition trading portfolios on the specific information in question.

5. Implications and directions for future research

Fama (1998) argues that the roughly equal prevalence of under- and overreactions in empirical research implies that market prices are informationally efficient. This claim is correct only if we are unable to predict the situations in which we will observe under- and overreactions. Our experiments show that we can make such predictions in the laboratory, simply by knowing the reliability of investors' information. Consistent with 'moderated confidence', experiments 1 and 2 both show that prices and investors' value estimates tend to underreact more as the reliability of information increases.

[5] In experiment 1, investors had only one signal. Consequently, their valuation task was somewhat simpler, and not surprisingly they produced prices that fell on the wrong side of 50 only 11% of the time. Nevertheless, this is enough to create an important difference between weak-form and semi-strong-form tests in experiment 1: when investors have less-reliable information weak-form tests reveal over-reactions that are statistically significant using all dependent measures we consider.

Any anomaly shown in the laboratory leads one to ask whether the same results would be observed among investors with greater experience. Several arguments convince us that they would. First, we analyzed our current data to search for experience effects, and found none. We performed two different analyses. For both experiments 1 and 2, we compared results between the first and last securities traded by each cohort. For experiment 1 we also compared results between those cohorts that traded low-signal-reliability securities first (and high-signal-reliability securities second) and those cohorts that traded high-signal-reliability securities first (and low-signal-reliability securities second). In all analyses, experience was never significant, and we saw no systematic evidence that effect magnitudes decreased with experience. We also note that experiment 2 is conducted with the same participants in experiment 1. The results of experiment 2 are largely consistent with those of experiment 1. Thus, the experience that participants get in the experiments we report does not seem to have much effect on the results.

Most experiments that examine experience, as well as most formal learning models, show that experience effects are largest when the learners are first getting their experience (i.e., over the interval we examine). After some time, the learning curve flattens. Many papers in psychology have shown that overconfidence is a highly robust result, and is not easily eliminated with experience in a variety of settings. Thus, based on the above analysis, we believe it is unlikely that the results would vanish in additional trading sessions.

Moreover, to the extent that experience could affect our results in additional sessions, it seems most likely to reduce the magnitude of the effects we observe, rather than their directions. Thus, experience is unlikely to affect the *pattern* of over- and underreactions that we observe across cells of our experimental design. Because it is such differences across treatments, rather than absolute levels, that are most easily interpreted in experiments, we do not believe that data from more experienced participants will change the inferences we draw from the study. In particular, we would expect that investors would be more likely to underreact and less likely to overreact to information, as that information becomes more reliable.

Finally, even if experience did reduce the magnitude of our effects, we do not believe that such a result would make the present results uninteresting. Financial markets always have some inexperienced traders, and it is useful for research to shed light on the errors such traders are likely to make. Efficient markets theory suggests that more-experienced traders will compete to eliminate such errors, but experimental evidence and theoretical models suggest that this might not always happen (e.g., Benos, 1998; Camerer, 1987; De Long et al., 1991; Fischer and Verrecchia, 1999; Kyle and Wang, 1997). This is an interesting question, but one that is distinct from the questions we examine in our study.

Overall, our experimental results have some interesting implications for how the anomalies literature should be interpreted. Many studies that condition on non-price-related information show underreactions. Markets appear to underreact to earnings announcements (e.g., Bernard and Thomas, 1989, 1990), dividend changes (Michaely et al., 1995), analyst reports (Womack, 1996), and measures of earnings quality (Sloan, 1996). In contrast, Lakonishok et al. (1994) are rather exceptional in showing an overreaction using purely non-price information to form portfolios: they show overreactions to five-year sales growth rates.

The prevalence of underreactions in event studies might arise because researchers direct their attention toward information releases and events that contain relatively reliable information about future performance. It is also possible that whatever effect causes underreactions to be more severe than overreactions in our markets, as well as the markets of Bloomfield (1996a, b) and Gillette et al. (1998), also has a similar effect in larger markets. However, our experiment was not designed to explore this tendency toward underreaction.

Many empirical studies showing overreactions form portfolios that are formed on the basis of market prices rather than information. For example, De Bondt and Thaler (1985, 1987) claim to observe overreaction, because stocks with high past returns are priced too high and stocks with low past returns are priced too low. Our second experiment shows a similar pattern of results, even though investors are actually strongly underreacting to reliable information, and overreacting to unreliable information only slightly, if at all. We believe that weak-form overreactions are driven by noise in prices that are unrelated to the available information. These overreactions cancel out when information is used to form portfolios, but result in systematic biases when price levels or returns are used to form portfolios (because high prices are associated with positive price errors).

Our study indicates several ways in which empirical research could test directly for moderated confidence. Our results suggest that market prices will overreact to information that is determined to be unreliable and underreact to information that is determined to be reliable. For example, if markets underreact to earnings because earnings is a relatively reliable indicator of value, then underreactions to earnings changes should be larger for firms and industries in which earnings changes are more reliable value indicators. In contrast, overreactions to widely publicized events should be larger when those events have less value relevance.

Empirical researchers could also attempt to assess the extent to which moderated confidence in financial markets is rational. Any evidence of moderated confidence is irrational in our laboratory markets, because investors have perfect information on signal reliability (they know the number of times the relevant coin was flipped). Evidence of moderated confidence in empirical studies could be rational if investors assess information reliability as accurately as possible given the information available to them. The first step toward testing the rationality of moderated confidence would be to use information *available at the time of portfolio formation* to assess information reliability. If investors could have determined information reliability at that time, they should have been able to exploit overreactions to unreliable information and underreactions to reliable information.

Finally, future research might attempt to integrate our view of moderated confidence with recent models of overconfidence in the literature. For example, moderated confidence might also be used to re-characterize the 'regime-shifting' model of Barberis et al. (1998). They assume that earnings follow a random walk, but that investors believe that the earnings process switches between a mean-reverting regime in which earnings changes are negatively autocorrelated and a continuing regime in which those changes are positively autocorrelated. This model is roughly equivalent to assuming that investors overestimate the reliability of the (relatively unreliable) information about the time-series parameters of earnings that can be extracted from a short sequence of earnings changes.

Also, the 'overconfidence' models of Daniel et al. (1998a, b), Gervais and Odean (1997), and Odean (1998) predict that investors will overreact to all information because they overestimate its reliability. Our results suggest this assumption may not generalize to settings in which investors are given information of high reliability. It would be helpful to know how a more generalized view of inaccurate confidence would affect the results of those models.

Appendix A. 'Clearinghouse' market

A.1. Excerpts from instructions to investors

Overview. During this session, you will trade shares of many securities. Each security pays a single final dividend of between 0 and 100 'francs,' which are a laboratory currency. This sum is referred to as the security's 'true value'. You will not be told the true value of a security until trading in that security is over. Whenever you sell a share for more than true value or buy a share for less than true value, you gain francs. Whenever you sell a share for less than true value or buy a share for more than true value, you lose francs. At the end of the session, we convert the number of francs you gain or lose into U.S. dollars.

Entering a demand schedule. In each round of trading, you will choose a demand schedule that states for each possible price how many shares you wish to buy or sell (up to a maximum of 50 shares). You set this demand schedule by choosing two numbers:

1. The price at which you do not want to trade any shares (your *reservation price*).
2. The change in the number of shares you want to trade for every 1-franc decrease in price (the *angle* of your demand schedule).

Choosing these two numbers results in a complete demand schedule.

How trade occurs. Once everyone has entered a demand schedule, a central computer determines the 'market-clearing price' at which the total number of shares bought equals the total number sold. If there is a range of market-clearing prices, the computer chooses the middle one. The computer then uses your demand schedule to determine how many shares you bought or sold at that price. You will then see the following information:
(1) the market-clearing price;
(2) the total number of shares traded at the market clearing price ('volume')
(3) the number of shares you personally traded in that period; and
(4) your cumulative holdings in shares and cash through the last round.
At the beginning of trading in each security, you are shown as having no cash and no shares. However, you can still buy or sell up to 50 shares in each round, regardless of the amount of shares and cash that you have. At the end of trading in each security, each share you hold is converted into from 0 to 100 francs, depending on the share's true value.

Estimating the value of the security. In every round of trading, you will be asked to estimate the true value of the security. Please consider this estimate carefully. It is very useful to our research, and will also help you trade more wisely.

Determining Your Winnings. At the end of trading in a security, you will learn its true value. Every share you trade changes your wealth in francs according to the formulas

$$\text{BUYING:} \quad \text{Change in Wealth per share} = (\text{Value} - \text{Price}),$$

$$\text{SELLING:} \quad \text{Change in Wealth per share} = (\text{Price} - \text{Value}).$$

Your cash winnings will be determined by the number of francs you gained or lost over the course of the session. Francs are converted into cash according to the formula

$$\text{Dollar winnings} = (\text{Gain or Loss in francs} + \text{'Floor'})\text{Conversion Rate}.$$

You will not learn the floor or conversion rate. However, these parameters are set so that the average winnings will be approximately \$30 per session. If you earn too few francs you are given a minimum payment of \$10. Note that because the floor is positive, you can win money even if you lose francs. Thus, you can increase your winnings by either winning more francs or losing fewer francs.

A.2. Information for securities 1–2 (practice securities)

To determine the value of each security, we use a question from a general knowledge test that has a correct answer between 0% and 100%. The value of the security (in francs) is equal to the correct answer (in percent). Thus, if the correct answer is 34%, the security will have a value of 34 francs. Everyone will always see the same question just before the second round of trading.

A.3. *Information for securities 3–7* (*experiment 1*) (*presented after trade of security 2 was completed*)

To determine the value of each security, we used a computer to simulate the random choice of coins from an enormous pile containing two types of coins. One type of coin is called 'heads-biased'. When flipped, heads-biased coins have a 60% chance of coming up heads, and a 40% chance of coming up 'tails'. The other type of coin is called 'tails-biased'. When flipped, tails-biased coins have a 40% chance of coming up 'heads', and a 60% chance of coming up 'tails', The pile has an equal number of heads-biased and tails-biased coins.

We flipped each coin some number of times. We tossed each coin into a bucket depending on how many heads and tails came up. *The value of each security (in francs) is equal to the proportion of those coins (in percent) that are heads-biased in that particular bucket.*

For example, you could be presented with a bucket of coins containing those that were flipped two time and came up heads once and tails once. If exactly 50% of the coins in this bucket were heads-biased, the value of the security would be 50 francs. If 45% of the coins in this bucket were heads-biased, the value of the security would be 45 francs, and so on.

Because the pile had an equal number of heads-biased and tails-biased coins, before you know how many times the coins in a bucket came up heads and tails, you would expect that bucket to have 50% heads-biased coins. However, once you see the results of coin flipping, you may want to alter your estimate of this probability for that specific bucket of coins: a bucket of coins that come up heads more often than tails is likely to include more heads-biased coins than tails-biased coins. Similarly, a bucket of coins that comes up tails more often than heads is likely to include more tails-biased coins than heads-biased coins.

For each security, we choose a new bucket. All three of the investors in your market will see the same information about the bucket on which that security is based, just before the second round of trading. Whatever information you see about the bucket is also seen by all of the traders in your market.

A.4. *Information for securities 8–14* (*experiment 2*) (*presented after trade of security 7 was completed*)

For the next 6 securities, security value (in francs) is equal to the average of the percentages of heads-biased coins in TWO buckets. For example, if one bucket has 30% heads-biased coins, and the other has 50% heads-biased coins, then the AVERAGE proportion is 40%, because (30% + 50%)/2 = 40%. The value of this security would be 40 francs.

Similarly, if one bucket has 70% heads-biased coins, and the other has 60% heads-biased coins, then the AVERAGE proportion is 65%, because (70% + 60%)/2 = 65%. The value of this security would be 65 francs.

You will receive information about each bucket in the same way that you received information about each bucket in the previous securities. All other aspects of the setting are exactly as they were before. The switch from one bucket to two buckets is the ONLY change.

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