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Price Movements as Indicators of Tender Offer Success

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ABSTRACT

This paper examines movements in the prices of target stocks as predictors of the ultimate success or failure of tender offers. An empirical investigation of 100% cash tender offers during the years 1976 to 1981 leads to the conclusion that, with few exceptions, market prices are well-calibrated, i.e., the current target price during the offer period measures the expected (discounted) stock price at the conclusion date. The market's probability predictions improve monotonically over time.

WITHIN THE PAST FEW years, the pace of corporate acquisitions has increased dramatically. This activity has renewed academic interest in explanations for these acquisitions and in measurement of the associated impacts on the acquiring and acquired firms. For instance, it is customary to predict that acquisitions are motivated by value-maximization behavior and to test whether gains accrue to target and acquiring company stockholders as a result. In recent surveys, Halpern [7] and Jensen and Ruback [9] offer extensive reviews of the evidence on these points. Key tests of the value-maximization hypothesis are provided by Dodd and Ruback [6], Bradley [2], and Bradley, Desai, and Kim [3]. The collective evidence of these "event" studies indicates that when a tender offer is made, target shares earn positive excess returns (relative to the predicted return accounting for market movements).

In the present paper, the tender offer evidence is put to a different test. Price movements in the target company's stock during the offer period are evaluated as predictors of the ultimate success or failure of the tender.[1] If the tender is successful, the target stock will trade at (or very near) the tender price before being delisted. If the tender proves to be unsuccessful, the stock will trade at a significantly lower value. Prior to the conclusion date of the offer, daily movements in the target stock price represent the collective opinion of the market participants as to the success or failure of the offer. Consequently, these price movements, one might expect, would presage the ultimate outcome of the offer. In particular, the greater the increase in the target stock price, the greater the "market odds" of a successful tender offer. (These market odds are determined

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[1] In a study of tender offers by multiple bidders, Ruback [12] considers (but does not estimate) the implied market probability that an initial offer will be successful. However, to our knowledge, the present study is the first to examine the probabilistic predictions of tender success implied by target stock price movements and to test the performance of these predictions.

to allow a typical shareholder a normal rate of return on the target shares.) Probability forecasts for the tender outcome can be inferred from these price movements and compared with the actual frequency of tender success. In this way, the information content of target price movements is evaluated.

In turn, the observation that the current market price reflects the market odds of success is the basis for an analysis of the potential excess returns available from an optimal investment policy in the target shares. Consider the trading strategy of an investor during the offer period, i.e., after the offer announcement date and up to the offer conclusion date. At any time during this period, the investor observes the current price of the target shares and infers the corresponding market odds of success. Based on whatever information is at his or her disposal, the investor formulates an assessment of the odds of tender success. Then if the investors' own odds of success are greater (less) than the market odds, they can earn an excess rate of return by purchasing (selling short) the target shares. The present study carries out such a comparison week by week during the offer period, taking the past frequency of tender offer success over a sample of target firms as the basis for the investor's assessed odds of success. (Thus, no excess returns are available if the market odds implied by the current price match the observed frequency of success in the sample.) More generally, the approach allows the investors' assessed odds of success to be based on any and all types of information. In turn, if new information was to be acquired, investors would revise (in a Bayesian fashion) their odds and investment strategies accordingly.[2]

An empirical investigation of 100% cash tender offers during the years 1976 to 1981 results in the following conclusions:

1. Movements in target stock prices are informative of the success or failure of the tender. The larger is the increase in the relative stock price, the greater is the chance of tender success.
2. The market's probability predictions improve monotonically over time (i.e., as the conclusion date nears).
3. With few exceptions, market prices are well-calibrated, i.e., the current target price during the offer period reflects the expected (discounted) stock price at the conclusion date.

I. Market Predictions

Our analysis pictures the tender offer in a simple way. The would-be acquiring firm makes a formal offer to the stockholders of the target firm; the offer is outstanding for an amount of time; finally, the offer is resolved either with the success or failure of the tender. (Our sample of tender offers excludes competitive tender offers and tenders which met with only partial success. The potential bias

[2] The Bayesian viewpoint also sheds light on the difference between the present approach and that of previous studies of price movements associated with tender offers (see Jensen and Ruback [9]). Past studies have taken an ex post point of view, examining realized excess rates of return (stemming from target stock price movements) conditional on tender success or failure. Our study takes the converse (ex ante) point of view, focusing on the probability of tender success or failure, conditional on current price movements.

caused by limiting the sample in this way will be discussed later.) In short, the tender outcome is viewed as a simple binary event—success or failure—and a test of the market's ability to predict this outcome during the offer period (prior to the tender's resolution) is conducted.

Consider first the impact on value resulting from the tender. If the offer is successful, target shares will trade at the tender price (before the stock is delisted). If the tender is unsuccessful, the target shares will settle at a new market-determined "fallback" price. Analysis of the unsuccessful offers shows that the target price following the expiration of the offer can be relatively well-predicted, settling above the market price prevailing before the offer but below the tender price.

Given the value consequences of these twin outcomes, it is possible to infer the market's probabilistic prediction of success (or failure) from movements in the target's stock price. Let P_d denote the target stock price at day d during the offer period which begins at announcement date $d = 0$ and extends through the conclusion date, $d = D$. If after the announcement, the stock price immediately jumps to the tender price, P_T, one can infer that the market predicts the tender will be successful with certainty. Alternatively, a minimal movement to a level no higher than the fallback price, P_F, implies that the market assesses a zero probability of success. In general, the larger is the price increase in the interval $[P_F, P_T]$, then the greater is the market's probability of success.

The main test of the predictive value of stock price changes rests on the following hypothesis.

On any day during the offer period, the current price of the target stock measures the expected value of the stock price at the conclusion date.

Since at date D the target stock will be worth P_T or P_F, depending on the success or failure of the tender, the simplest version of the expected value hypothesis predicts

$$P_d = qP_T + (1 - q)P_F, \tag{1}$$

where q denotes the probability that the offer is successful. Probability q, of course, is not directly observable. The point is that with a known value of P_T and an estimate of P_F, the market probability of success can be easily inferred. Rearrangement of (1) yields

$$q = [P_d - P_F]/[P_T - P_F]. \tag{2}$$

The inferred probability of success is measured by the percentage amount that the stock price increases above the fallback price and toward the tender price. If, after the tender announcement, the stock price immediately jumps to the tender price, the market probability of success is one. On the other hand, if there is no movement above the fallback price, the inferred probability of success is zero. In general, an $x\%$ relative price increase implies an $x\%$ probability of success.[3]

[3] It is worth re-emphasizing the necessity of restricting the sample to noncompeting tender offers. In the case of competing tenders, the target's stock price commonly rises above the initial tender price in (correct) anticipation of subsequent higher bids. Here, it is impossible to estimate the probability of the initial tender's success without a prior estimate of the level and likelihood of subsequent tender(s).

Since the offer period can extend over a significant period of time, Equation (1) needs to be modified slightly to account for the time value of money:

$$P_d = [qP_T + (1 - q)P_F]/[1 + r_f], \tag{1'}$$

where r_f is the required rate of return to be earned over the holding period d to D. If the success or failure of the tender offer is uncorrelated with market movements, then r_f would be the prevailing risk-free rate of return.[4] The inferred market odds become

$$q = [(1 + r_f)P_d - P_F]/(P_T - P_F]. \tag{2'}$$

Under the expected value hypothesis, the target's current price plays exactly the role of a futures price relative to date D. Thus, if Equation (1′) holds, a trader whose information is no better than the market's can expect to earn a zero excess rate of return on average. Moreover, under the hypothesis, it immediately follows that the target's stock price should fluctuate randomly over the holding period (Samuelson [13]). Indeed, random fluctuations should be expected even though the stock's trading price will surely gravitate to P_T or P_F as conclusion date D nears.

A. Evaluating Market Forecasts

Under the expected value hypothesis, the record of daily target prices during the holding period provides a set of probabilistic forecasts as to the likely success or failure of the tender offer. Indeed, one might emphasize the point by likening these forecasts to the daily predictions of a human forecaster, say, a meteorologist predicting the weather (rain or shine) for a fixed future date. Whatever the source of the forecast, a simple evaluative test would compare the probabilistic predictions against the actual observed frequency of outcomes. It is easy to see that the expected value presumption is equivalent to the following hypothesis.

Over each subsample of predictions for which the market rates a q probability of success, the ex post observed frequency of success is also q.

In short, if a given price increase implies q as the market probability of success and if this prediction is *validated* by a matching success frequency, then the expected value hypothesis is confirmed.[5]

To carry out a test of this hypothesis, it is necessary to group the set of predictions into a limited number of discrete categories. For instance, one could restrict the predictions to the eleven decimal categories, $q_0 = 0.0$, $q_1 = 0.1$, $\cdots$, $q_{11} = 1.0$ and then record the ex post frequency of success, z_j, for each category. The expected value hypothesis implies $z_j = q_j$ for all categories j, i.e., each q_j is an unbiased predictor of z_j.

[4] A retrospective examination of the six-year sample of tender offers bears out this presumption. Over the 109 companies, the correlation between the success ($s = 1$) or failure ($s = 0$) of the tender offer and the market movement over the period is 0.07 with a p-value of 45%. Thus, the null hypothesis of zero correlation (which we adopt henceforth) is strongly confirmed.

[5] Strictly speaking, the hypothesis maintains that the observed frequency of success should be arbitrarily close to the market prediction for sufficiently large sample size.

B. The Brier Score

Considerably more than "unbiasedness" is required for "good" forecasts. To bring out this point, we will consider a widely employed measure of forecast performance, the Brier score [4]. In the case of only two outcomes, success or failure, the Brier score is defined as

$$B = [\sum_{i=1}^{I} (q_i - s_i)^2]/I, \tag{3}$$

where I is the number of forecasts, q_i is the predicted probability that the ith tender offer will be successful, and s_i is the offer's actual outcome, $s_i = 1$ for success and $s_i = 0$ for failure. In simplest terms, the Brier score represents a standardized measure of the mean-squared error associated with the forecast.

The more accurate are the forecasts on average over the sample, the lower the Brier score. Thus, "perfect" market forecasts always quote $q = 1$ for successful tenders and $q = 0$ for unsuccessful ones implying $B = 0$. At the opposite extreme, forecasts which are always dead wrong ($q = 1$ when $s = 0$ and $q = 0$ when $s = 1$) generate a maximum score, $B = 1$.[6] In the case of a purely random event (let's say, the toss of a coin), the prediction $q = 0.5$ would imply $B = (0.5)^2 = 0.25$. In the sample of tender offers below, the overall frequency of success is about 75%. A prediction of $q = 0.75$ implies $B = 0.1875$.

Additional insight into forecast performance can be gathered by employing Murphy's [11] partition of the Brier score:

$$B = z(1 - z) + \sum_{j=1}^{J} f_j(q_j - z_j)^2 - \sum_{j=1}^{J} f_j(z_j - z)^2, \tag{4}$$

where z is the overall frequency of success across the sample and f_j is the frequency of forecasts falling in probability category j, $j = 1, \cdots, J$. Only the last two terms depend on the probability forecasts themselves. The first term is a function of the overall or base-rate probability of success across the sample. The second term is a measure of *calibration* reflecting the extent to which forecasts across the categories are unbiased; it is zero if and only if $q_j = z_j$ for all categories j. The third term captures the degree of *resolution* of the predictions, as measured by the frequency of forecasts in which the proportion of successes is different from the overall proportion. The greater the degree of resolution, the larger the reduction in the Brier score. In general, there is a tradeoff between the second and third terms. Consider "nondiscriminating" forecasts where $q_i = z$ for all predictions i. For instance, a meteorologist might forecast a z probability of rain for each day in the month of May where z is the average proportion of rainy days in the month. Clearly, such forecasts are of very little *daily* value. Nonetheless, they are perfectly calibrated. In the Brier score, both the second and third terms will be zero. A more discriminating forecaster could improve upon this performance by making differential daily forecasts and so raising the third term of the

[6] Of course, if properly interpreted, a forecast that is perfectly negatively correlated with a true outcome is of maximum value to an investor. A perfect forecast (with Brier score $B = 0$) is obtained by reversing the prediction.

partition. Provided that the forecasts remain well-calibrated, the improved discrimination will reduce the Brier score. However, if the ability to discriminate in this way is illusory, increases in the second term due to miscalibration will more than offset reductions in the third term, causing the Brier score to increase. In short, the Brier score encourages forecast discrimination as long as calibration is unimpaired.

C. A Bayesian Footnote

In the preceding pages, we have described how the probabilistic "market" forecasts can be inferred from observed price movements and how these forecasts can be evaluated. It is important to point out that this procedure is wholly consistent with Bayesian revisions in probability. The Bayesian forecaster starts with a prior judgment about the likelihood that a given tender offer will prove successful. Then, additional information bearing on the success of the tender offer becomes available—the record to date of daily prices over the offer period. In light of this information, what is the probability of tender success? One would naturally look to historical data on tender outcomes and price movements to answer this question. However, the answer depends on how one "codes" the information in the price series. For instance, an initial presumption might be that knowledge of the current stock price is sufficient for the probability revision, i.e., the precise sequence of past daily prices is irrelevant. This coding presumption is tractable and consistent with the efficient market hypothesis. A second presumption is that only the relative price increase matters, i.e., the current price should be measured vis-à-vis the initial price level, P_I, and the tender price, P_T. Thus, for purposes of probability revision, a sufficient price statistic would be $\rho = [P_d - P_F]/[P_T - P_F]$. This is a simple and reasonable coding of the price data, but it is clearly not the only one. Equation (2′) indicates a slightly different coding. Still another coding might incorporate information on the duration of the offer. If successful offers tend to be concluded more quickly, such data would be informative.

Whatever the price coding, the Bayesian forecaster judges the probability of success in light of ρ to be

$$\text{Prob}(\text{suc} \mid \rho) = \frac{\text{Prob}(\rho \mid \text{suc})\text{Prob}(\text{suc})}{\text{Prob}(\rho \mid \text{suc})\text{Prob}(\text{suc}) + \text{Prob}(\rho \mid \text{fail})\text{Prob}(\text{fail})}.$$

The forecaster's revised probability of success depends on the prior probability he ascribes to that event and on the relative likelihood of generating ρ in the cases of successful and unsuccessful tenders. This prior probability and the pair of likelihoods can be assessed separately, and if either changes, so too will the forecaster's revised probability estimate.

In assessing the prior probability and the likelihood function, it is natural to appeal to the sample evidence. Lacking information to the contrary, one would take the overall frequency of success across the sample as the appropriate prior probability. In turn, the observed frequency of ρ over the samples of successful and unsuccessful companies would serve as proxies for $\text{Prob}(\rho \mid \text{success})$ and $\text{Prob}(\rho \mid \text{failure})$, respectively. It should be evident that computing

Prob(success | ρ) directly from the sample or calculating this revised probability from Bayes' theorem using empirically based likelihoods and prior is a matter of indifference. The two methods are equivalent. In the following section, the former approach is taken.

II. Empirical Results

The data consists of a sample of 109 tender offers during the years 1976 to 1981. All members of the sample had the following characteristics.

(a) The offer was a cash tender for 100% of the target's outstanding shares.
(b) The tender price was at least 15% higher than the target's average stock price two weeks prior to the offer announcement date.
(c) There were no competing tender offers.
(d) The target firm was not a bank, insurance company, or utility.
(e) The target firm's common stock was traded on the New York or American stock exchange.

The restriction to 100% cash offers in (a) was designed to minimize the uncertainty in the valuation of the tender offer. Thus, stock swaps, bond swaps, and partial tenders were excluded. A 15% minimum price premium was required to ensure that there would be a significant range for price movements during the offer period. As indicated earlier, the restriction to non-competitive tender offers is essential to the calculation of market forecasts. Finally, requirement (d) was imposed to ensure that the offer would not be subject to significant regulatory delay.

For each target firm in the sample, the following information was compiled: the tender price, the success or failure of the tender offer, and the daily trading prices of the target stock during the offer period. Tender prices and outcomes, and offer dates were taken from the Tender Offer Data Bases provided by Douglas Austin [1] and Kidder, Peabody and Co. [10]. Dates for the offer period in these files were checked against the tender announcements published in the *Wall Street Journal.* Finally, all prices were computed using an initial price obtained from the ISL Daily Stock Price Series and rates of return obtained from the daily CRSP file.

A. Fallback Prices

In order to carry out the empirical tests, it is necessary to generate estimates of P_F, the price of the target stock in the event that the tender offer is unsuccessful. Obviously, estimates of P_F are available only for the sample of unsuccessful offers. Our method is to construct an estimation equation for the fallback price using the sample of unsuccessful offers and to apply this equation to the successful targets. Thus, the key assumption is that the fallback behavior of the unsuccessful targets is representative of the behavior for the sample of successful targets, had tenders for those targets failed.[7]

[7] In making this presumption, we are again taking an ex ante point of view. While it is true that the offers in the successful sample did not fail ex post, the issue is what would have been their

The simple estimation equation posits that the fallback price depends linearly on P_T, the tender price, and on P_I, the initial stock price prevailing prior to the tender announcement.[8] Thus,

$$P_F = a_0 + a_1 P_I + a_2 P_T. \tag{5}$$

In addition, it was posited that this relationship should be independent of the nominal levels of P_T and P_I (i.e., the market does not suffer from money illusion) and that P_F should lie in the interval $[P_I, P_T]$, implying the restrictions $a_0 = 0$ and $a_1 + a_2 = 1$. In short, the prediction is that the fallback price will be a weighted average of the initial stock price and the tender price. Based on the sample of unsuccessful stocks, the following constrained regression equation was estimated:

$$\begin{aligned} P_F = {} & \underset{(15.0)}{0.63P_I} + \underset{(9.0)}{0.37P_T}, \\ & R^2 = 0.99, \end{aligned} \tag{6}$$

where t-ratios are shown in parentheses, and the restriction $a_1 + a_2 = 1$ could not be rejected at the 10% significance level.[9,10] (Here, P_F was measured as the three-day average stock price during the second week following the failure of the tender, and P_I was the three-day average price two weeks prior to the announcement date.) In the wake of a failed tender, the stock price does not revert to the initial price but rather stays significantly above its old level. This result provides some evidence in favor of the hypothesis that the tender offer provides the market new information about the potential value of the target. The market neither accepts the tender price as the true valuation nor discounts the tender completely.

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fallback behavior *had they failed*. It seems reasonable to extrapolate the results from the unsuccessful sample to the successful one under normal circumstances—as when the success or failure of the offer depends on the degree of entrenchment of current management or on antitrust considerations. However, it is also possible that the successful sample would display *lower* fallback prices than the unsuccessful sample due to the presence of selection bias. Offer success may be due in part to the fact that target shareholders ascribe relatively lower values to the firm under current management. If target shareholders are right in their prediction and if this effect is important, it would imply lower fallback prices for the successful sample, and thus, higher market odds predictions [via Equation (2′)], other things equal. A modification in this direction would improve the match between the market odds and the ex post frequency of tender success, and, thus, would provide stronger evidence in favor of the expected value hypothesis.

[8] An alternative forecast of P_F would be based on explanatory variables P_T and $P_I(1 + \bar{r})$, where $\bar{r}$ is the return on the target over the offer period estimated from the Capital Asset Pricing Model according to $\bar{r} = r_f + \beta(r_m - r_f)$. When tested, this formulation was found to provide no better estimates of P_F over the sample of unsuccessful stocks nor to generate more accurate probability forecasts. Consequently, the simpler formulation in (5) was maintained.

[9] We are aware that the error terms in (6) are likely to be subject to heteroscedasticity. As a check, we also estimated the transformed equation: $P_F/P_I = a_1 + a_2(P_T/P_I)$. By removing nominal price levels from the equation, this specification should also solve the heteroscedasticity problem. For the transformed equation, the restriction $a_1 + a_2 = 1$ continued to be accepted, and the coefficient t-values remained highly significant.

[10] The implicit assumption in this estimation procedure is that the regression relationship is stationary during the years surrounding the sample period. Clearly, in the first year of the sample period, 1976, the market forecast of the fallback price can only depend on previous years' data and not on an estimated relationship using a sample of target offers yet to come.

On average, the stock price increases some 37% of the way toward the tender price in the event of a failed offer.[11]

Since the market assessment of the odds of tender success depends directly on the forecast of the fallback price, errors in estimating the latter will lead to errors in the former.[12] Although the prediction of the fallback price is subject to error, a routine sensitivity analysis indicates that calculated market odds are relatively insensitive to the precise estimated relationship. For instance, if the estimate of P_F in Equation (6) took the alternative form $P_F = 0.75P_I + 0.25P_T$, then the market odds, q, increase by an average of 0.125, for q varying between zero and one. Conversely, an increase in the estimate of P_F lowers the market odds.

B. Prices and Predictions

From the previous regression results, the fallback price for each of the 109 stocks in the sample was estimated as $P_F = 0.63P_I + 0.37P_T$. For successful stocks, P_F provides a prediction of the target stock's price had the tender failed. Then using P_F and P_T and Equation (2′), we calculated success probabilities for each target company and for each trading day during the offer period. The risk-free rate of return, r_f, was taken to be the return on U.S. thirty-day Treasury bills compounded daily over the holding period, $D - d$.

Our main tests of these market forecasts employ time series of target stock prices during the offer period disaggregated by day or week. Since the length of the offer period varied considerably over the sample of stocks, we constructed the time series by the following means. The data was organized both by looking forward from the announcement date and backward from the conclusion date. Thus, the daily time series was constructed for forward days $d = 1, 2, \cdots, 30$ and backward days $d = -30, -29, \cdots, -1$, where the minus sign indicates days before the resolution of the offer. This bipartite procedure was expressly employed to preserve sample size for the statistical tests to be carried out. As of $d = 30$ (or $d = -30$), the offer period had already expired for 26 of the stocks leaving 83 stocks in the sample.[13]

Figure 1 summarizes the average daily prices for successful and unsuccessful stocks for $d = 1, 2, \cdots, 30; -30, \cdots, -1$. The left-hand scale measures the

[11] A comparison of other studies' findings is instructive. Bradley [2] analyzes the price behavior of unsuccessful offers during an earlier time period. In his sample, stockholders rejected the tender anticipating higher competing offers, an expectation that was validated in the market by target stock price increases of some 15% above the initial tender price. Bradley, Desai, and Kim [3] found that target stocks earned significant negative cumulative average returns during the period following an unsuccessful tender. Although this last study's methodology and target sample differed significantly from ours (making comparisons difficult), the evidence is consistent with our finding of a predictable target stock price decline following unsuccessful tenders.

[12] Besides the summary of statistics accompanying Equation (6), it is instructive to consider additional evidence concerning the estimation accuracy of P_F. The magnitude of the relative estimation error, $|\hat{P}_F/P_F - 1|$, averages 10.2% over all unsuccessful offers. The largest errors occurred in the case of a single stock with a fallback price nearly equal to the tender price and in the cases of four stocks with fallback prices within 5% of the initial price, P_I (two of which exhibited $P_F < P_I$). The average fallback price was 23% above the initial stock price.

[13] The duration of the offer periods varied over the sample as follows: 20 to 40 trading days (31% of the sample), 40 to 60 days (27%), greater than 60 days (22%), and less than 20 days (8%).

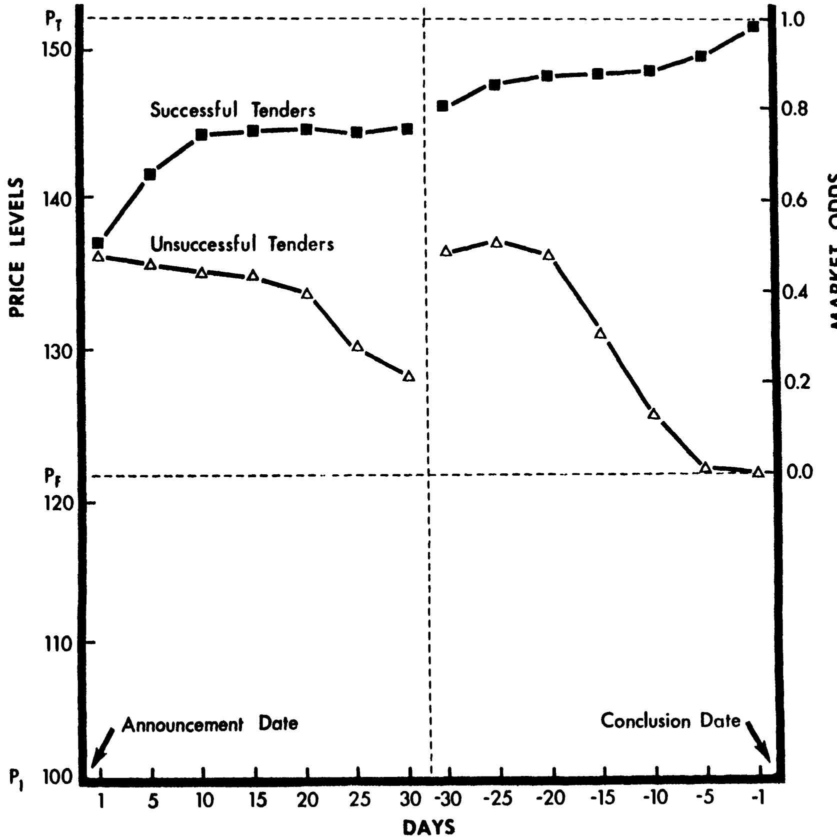

Figure 1. Average Price Levels

average percentage price increase relative to the initial price P_I. The right-hand scale lists the associated average probability of success. The figure shows that successful stocks show price increases of some 37% on average immediately following the announcement date. Prices continue to rise steadily toward the tender price as the offer period progresses. The pattern for unsuccessful stocks is quite different. The average immediate price jump is slightly less, about 35%. Then the average price starts a steady decline. On day 20, the price level is only about 30% above P_I. Finally, for the 10 days prior to the conclusion date, the average trading price returns to P_F, about 20% above P_I.

Although Figure 1 is useful in showing price trends during the offer period, it is also apt to present a misleading picture of the market's ability to distinguish successful and unsuccessful tenders. If all successful and unsuccessful offers tracked *precisely* along the respective price graphs, this fact, in itself, would provide *perfect* information about the tender outcome. Clearly, the average prices themselves would not be in equilibrium, since known successful stocks should immediately be bid up to P_T and known unsuccessful stocks bid down to P_F. However, within the respective samples of successful and unsuccessful stocks, there is considerable price variation. Indeed, if market prices are to be in equilibrium, then there must be enough overlap in the price distributions of successful and unsuccessful stocks to sustain "in-between" prices $p_d \in (P_F, P_T)$, which reflect genuine market uncertainty about the ultimate outcome of the tender offer.

This tender uncertainty is reflected in the probability forecasts associated with target prices via Equation (2′). To display these forecasts, it is convenient to divide the unit interval into six subintervals [0.0, 0.1), [0.1, 0.3), [0.3, 0.5), [0.5, 0.7), [0.7, 0.9), [0.9, 1.0], with each probability forecast assigned to the appropriate category. Henceforth, these will be referred to as the 0.05, 0.2, 0.4, 0.6, 0.8, and 0.95 probability categories. The number of categories was chosen with a mind to statistical limitations. Finer partitions, such as eleven decimal categories, make for weaker statistical tests. The more numerous observations in the 0.05 and 0.95 categories account for their narrower widths.

The distribution of weekly forecasts by probability categories for the samples of successful and unsuccessful tender offers is displayed in Figures 2A and 2B. (The weekly probability forecast was calculated as the five-day average of the daily forecasts.) In interpreting the figure, it is important to remember that a solid majority of the offers (some 76%) were successful. Thus, one would take this proportion as the "prior" probability of success for the typical target, provided, of course, that the sample is deemed representative of the larger population of tender offers over these years.[14] Given this prior probability, it is not surprising to find the bulk of the market forecasts falling into the 0.6, 0.8, and 0.95 categories, especially for the successful sample. For successful offers, the proportion of forecasts in these top categories increases over the twelve weeks. Indeed, the distribution of predictions for each week stochastically dominates (actually or virtually) the distribution of the preceding week. In week 1, 49% of the predictions are in the 0.8 and 0.95 categories, in week W−6, 84% are, and by week W−1, 98% are. For the unsuccessful offers, the weekly trend, as one would expect, is just the reverse, showing an accumulation of predictions in the 0.05 and 0.2 categories over time. Here, each weekly distribution (virtually) stochastically dominates the distribution of the following week. The proportion of predictions in the lowest two categories is 16% in week 1, 59% in week 6, and 76% in week W−1.

C. *Brier Scores*

Weekly Brier scores (including the base rate, calibration, and resolution components), for the market forecasts are shown in Table I. The conclusion to be drawn from the table is that the market's forecasting ability—as measured by the Brier score—becomes progressively better as the conclusion date nears. A

[14] The analysis of the accuracy of the market odds predictions is based on the entire sample period, 1976 to 1981. Consequently, the implicit assumption is that the frequency of tender success is stationary over these years. (If not, then the calendar year of the offer would itself be informative of the ultimate probability of success.) One finds that the stationary hypothesis cannot be rejected based on a two-part division of the sample (at January, 1979). Elsewhere, Jarrell and Bradley [8] present evidence that regulatory changes have strengthened the defense of targets against takeovers. The authors document a decline in the number of takeovers but do not provide evidence whether the probability of tender success has declined over time.

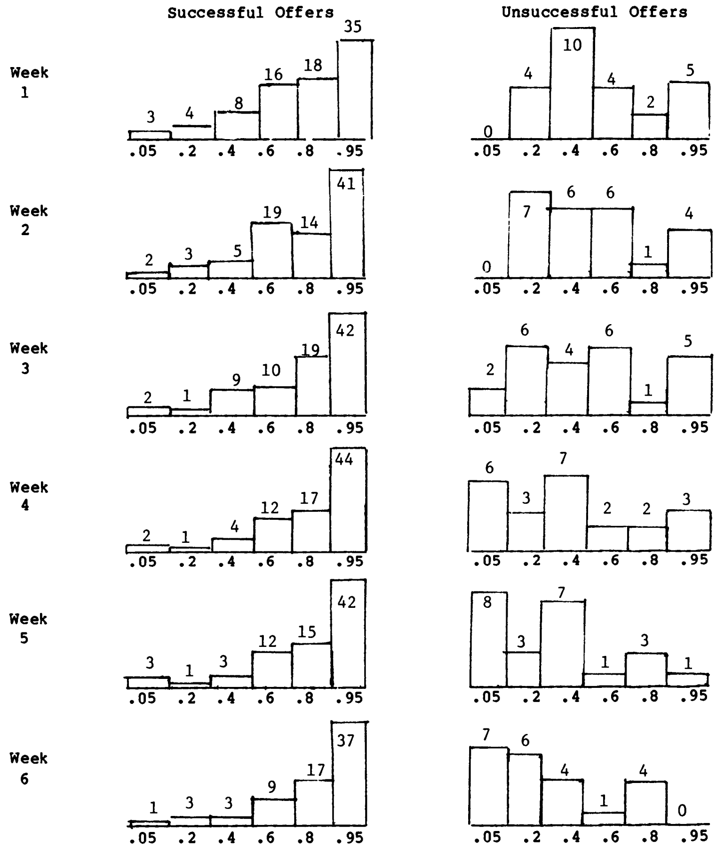

Figure 2A. Distribution of Forecasts—Weeks 1 to 6

Table I

Brier Scores

Week	Brier Score ($B = B_1 + B_2 - B_3$)	Significance Level	Base-rate B_1	Calibration B_2	Resolution B_3
1	0.194	(a) 0.75	0.177	0.049	0.032
2	0.161	(a) 0.30	0.173	0.031	0.043
3	0.158	(a) 0.25	0.174	0.029	0.045
4	0.125	(a) 0.02	0.173	0.018	0.066
5	0.119	(a) 0.005	0.178	0.024	0.083
6	0.118	(a) 0.005	0.182	0.023	0.087
W-6	0.121	(a) 0.005	0.182	0.028	0.088
W-5	0.120	(a) 0.005	0.178	0.025	0.083
W-4	0.105	(a) 0.005	0.173	0.020	0.088
W-3	0.093	(a) 0.005	0.174	0.019	0.100
W-2	0.051	(a) 0.005	0.173	0.006	0.128
W-1	0.043	(a) 0.005	0.177	0.009	0.143
12-Week Total	0.116	(a) 0.005	0.176	0.014	0.074

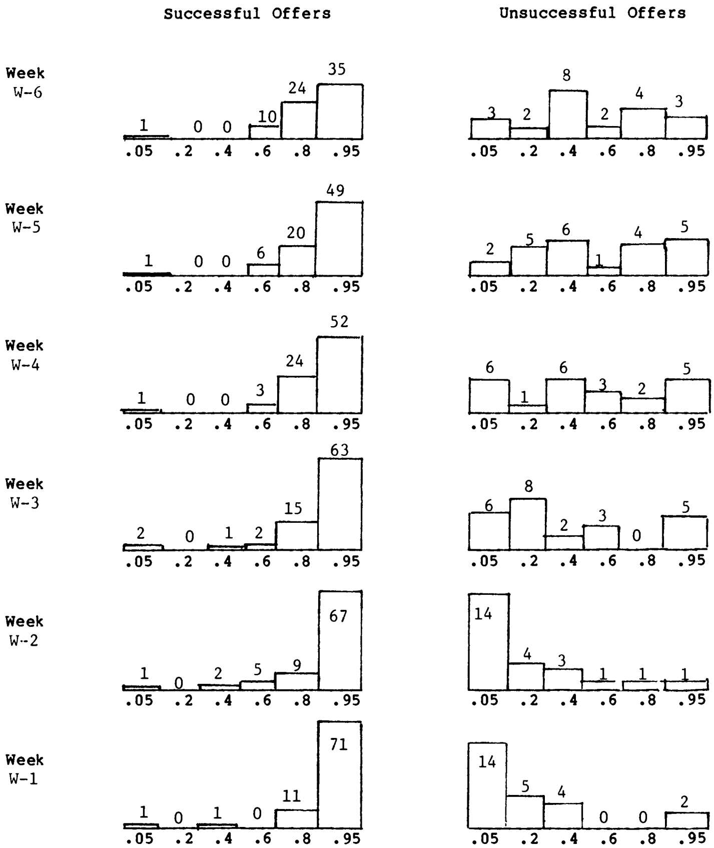

Figure 2B. Distribution of Forecasts—Weeks W−6 to W−1

convenient way to interpret the Brier scores is as follows: a Brier score of $z(1-z)$ is equivalent in terms of forecasting performance to a probability forecast of z which is right $z\%$ of the time. For instance, week 1's score of 0.194 is equivalent to a 74% forecast which is right 74% of the time, since (0.74) (1 − 0.74) = 0.194. Week W−6's score is equivalent to an 86% correct forecast, while week W−1's score is equivalent to a 95% correct forecast. Note that week 1's score is larger (worse) than the base rate component, B_1. If the market had simply used the base rate frequency of success to rate all stocks a 76% chance of success, it would have been right 76% of the time and attained a Brier score of 0.177. As gauged by stock price movements during the first week, the market showed a clear tendency to discriminate among the target stocks—marking some with a higher chance of success than 76%, others with a lower chance. On average, however, the market's attempt to discriminate during the first week resulted in poorer forecasting performance.

After week 1, the market's weekly Brier score was substantially lower than the base rate component, B_1. (Note that B_1 fluctuates slightly due to changes in z as the number of companies left in the sample changes.) Is this performance significantly better than simply making the base rate forecast? To answer this question, one can determine the likelihood that a correctly calibrated base rate forecast would score as low as the actual Brier result. This likelihood (based on an approximate chi-square test on a sample variance) is given in item (a) in Table I. After the first three weeks, one can reject the hypothesis that the base rate prediction is as good as the actual market forecast at the 2% significance level.

D. Resolution and Calibration

The source of the weekly improvement in forecasts lies in the last two terms of the Brier partition. Over time, both the calibration and resolution of market forecasts improves, the first term decreasing and the latter increasing. But of the two components, it is the resolution term which contributes most to the fall in the Brier score. Starting from a low level in the initial weeks, B_3 increases steadily thereafter (week W−5 excepted). It is worth noting that B_1 provides something of an upper bound on the degree of resolution; i.e., if all forecasts ($q = 0$ or $q = 1$) were perfect, then B_3 would be equal to B_1 and B would, of course, be equal to zero. Thus, it appears that the forecasts in the closing weeks exhibit close to maximal resolution. The same point emerges clearly from a review of the changing forecast distributions in Figure 2 where predictions accumulate at $q = 0$ and $q = 1$.

Now let us take a closer look at the calibration of market forecasts. Table II (A and B) summarizes the available evidence by providing a breakdown by probability category and week. Item (a) lists the statistic [no. of successes]/[total no. of cases]. A survey of these entries reveals a high correlation between these frequencies and the predicted probabilities. Consider the hypothesis that q_j is the true probability of success for tender offers falling into category j. Under this hypothesis, the number of successes follows a binomial distribution. Item (b) in the table lists p-values pertinent to this hypothesis when two-tailed rejection regions are employed. For the first cell, the p-value is given by $2(\text{Prob } y \geq 2) = 0.03$, where y is the number of successes. Across the table, very large p-values predominate, offering general support for the expected value hypothesis. In only 11 of the 72 cells can one reject the hypothesis that q_j is the true probability at the 20% level.

Because the power of the test is limited by small sample size, failure to reject the null hypothesis is not, of and in itself, overwhelming evidence in favor of market efficiency. As an alternative measure of calibration, Bayesian revised success probabilities are listed in item (c) of Table II (A and B). The revised probabilities are based on the observed sample given a prior probability distribution for q_j which is uniformly distributed on [0, 1]. It is well-known that, if the prior distribution of the unknown probability belong to the beta family (of which the uniform distribution is a special case), then under binomial sampling so too will the revised distribution. Given the uniform prior distribution, the revised success probability is given by $\hat{q} = [y + 1]/[n + 2]$, where n is the number of observations and y is the number of successes. Note that if no observations are taken, $\hat{q}$ equals 0.5, the mean of the uniform distribution.[15]

[15] As an alternative to the uniform distribution, one could employ a prior which reflects the overall

In a given cell, a comparison of q_j and $\hat{q}$ provides an alternative measure of calibration. For obvious reasons, the gap $q_j - \hat{q}$ is largest in those cells having the lowest p-values in item (b) (i.e., where the calibration hypothesis is most strongly rejected.)

E. Excess Returns

In a given instance, a gap between the market odds and the actual frequency of success (q_j and $\hat{q}$) signals a potential opportunity to earn excess returns from an appropriate investment strategy. We briefly consider the magnitudes of these returns. Our focus is restricted to the offer period itself and, consequently, excludes all "windfall" gains to target stockholders accruing before or immediately following the tender announcement. Rather, we examine the potential excess returns available to an "optimal" investor *after* the terms of the tender offer are public knowledge.[16]

In the case that $q_j < \hat{q}$ (i.e., the implied market odds are smaller than the ex post frequency of success), the target stock is *undervalued.* That is, purchasing target shares will generate an expected excess return: $\hat{r} > r_f$. More specifically, returns $\hat{r}$ and r_f are given by $[\hat{q}P_T + (1 - \hat{q})P_F]/P_d - 1$ and $[q_jP_T + (1 - q_j)P_F]/P_d - 1$, respectively. Subtracting one from the other, one obtains:

$$\hat{r} - r_f = [\hat{q} - q_j][(P_T - P_F)/P_d]. \tag{7}$$

The excess rate of return is proportional to $(\hat{q} - q_j)$, the difference between the investor's odds and the market's odds, and to $(P_T - P_F)/P_d$, the difference between the maximum and minimum possible rates of return on the investment.[17] Of course, if $q_j > \hat{q}$, then an excess return can be earned by selling the target short.

To illustrate the potential for excess returns, consider two of the entries in Table II (A and B) in which the largest gaps between q_j and q occur.

(i) In week 1, four targets with market odds in the 0.05 category (i.e., those whose market price barely rose above the fallback price) displayed a 0.50 rate of success. From (7), the calculated excess return over the average twelve-week holding period is 11.25%.

(ii) In week−6, twelve targets with market odds in the 0.6 category displayed

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75% success frequency across the sample. For instance, a beta distribution with parameters $y_0 = 3$ and $n_0 = 4$ generates a revised probability of $\hat{q} = [y + 3]/[n + 4]$. This alternative prior "pulls" the revised probabilities in the direction of 0.75 but in most cases does not significantly change the investor's expected returns.

[16] By contrast, previous research has documented the returns available to *long-term* holders of target shares. Consequently, the abnormal returns found in these studies include returns owing to the appreciation of shares before the announcement date, on the announcement date (where the immediate appreciation averages nearly 35% in our sample), and after the offer conclusion date.

[17] A complete analysis of excess returns would consider the proportion of the investor's portfolio to be devoted to purchases of target stocks. Note that such an investment has a large standard deviation, as well as a large return. This standard deviation is $\hat{\sigma} = [\hat{q}(1 - \hat{q})][(P_T - P_F)/P_d]$. Given that the success or failure of the tender offer is uncorrelated with the market, it is straightforward to determine the optimal proportion of the market portfolio to be devoted to the target stock. See Treynor and Black [14].

Table IIA

Calibration Tests—Weeks 1 to 6

	Probability Categories					
Week	0.05	0.2	0.4	0.6	0.8	.95
1 (a)	2/4	4/8	8/18	16/20	18/20	35/40
(b)	0.03	0.12	0.88	0.11	0.41	0.07
(c)	0.50	0.50	0.45	0.77	0.86	0.86
2 (a)	1/4	3/10	5/11	19/25	14/15	41/45
(b)	0.37	0.64	0.94	0.25	0.33	0.40
(c)	0.33	0.33	0.46	0.74	0.88	0.89
3 (a)	1/4	1/7	8/13	10/16	18/20	42/47
(b)	0.37	0.58(1)	0.20	0.53(1)	0.41	0.16
(c)	0.33	0.22	0.60	0.61	0.86	0.88
4 (a)	2/8	1/4	4/11	11/14	17/19	44/47
(b)	0.12	0.59(1)	0.53(1)	0.25	0.47	0.92
(c)	0.30	0.33	0.38	0.75	0.86	0.92
5 (a)	3/11	1/4	3/10	10/13	15/18	42/43
(b)	0.03	0.59(1)	0.76	0.34	0.50(1)	0.66
(c)	0.31	0.33	0.33	0.73	0.80	0.96
6 (a)	1/8	3/9	3/8	8/10	17/21	37/37
(b)	0.67	0.52	0.59(1)	0.33	0.60(1)	0.31
(c)	0.20	0.36	0.40	0.75	0.78	0.97

Note: item (a) lists [no. of successes/total no. of observations]. Item (b) lists the p-value pertinent to rejecting the hypothesis that q_j is the true success probability for targets in category j. In several instances (such as week 3, $q_j = 0.2$), the number of successes matches the median value of the distribution under the null hypothesis. In such a case, the entry 0.58(1) indicates the p-value for a *one-tailed* test of the hypothesis. Item c lists the revised probability of success for targets in category j based on the outcomes in item (a) and given a prior on q_j which is uniformly distributed on [0, 1].

a 0.78 rate of success. For this category, the expected excess return over the six-week holding period comes to 4.0%.

A caveat about these returns is in order. Viewed in isolation, each of the investment opportunities appears to offer significant excess returns. In the whole-sample context, however, this evidence is not surprising. Under the expected value hypothesis, one would expect that by chance alone one of the six cells in a given week would have a p-value of 20% or below. Across the whole of Table II (A and B), if the cell results were independent (which of course they are not), one would expect as many as 14 of 72 cells to fall below the 20% threshold. In fact, 11 cells fell into this category. In short, individual Bayesian probability estimates by cell overstate the potential excess returns.[18]

[18] The excess returns in (i) and (ii) accrue from selective investment in specified targets at specified times. By contrast, an across-the-board investment in *all* targets in the week following the tender announcement yields a modest excess return of 1.4% per target—a result which is consistent with Dodd's [5] finding of zero excess returns from tender stock investments immediately following the announcement. Moreover, while the excess returns in (i) and (ii) are substantial, the opportunities

Table IIB

Calibration Tests—Weeks W-6 to W-1

Week	Probability Categories 0.05	0.2	0.4	0.6	0.8	0.95
W-6 (a)	1/4	0.2	2/8	10/12	24/28	35/38
(b)	0.38	0.64(1)	0.64	0.16	0.60	0.66
(c)	0.33	0.25	0.30	0.78	0.83	0.90
W-5 (a)	1/3	0.6	1/5	6/7	20/24	49/54
(b)	0.28	0.52	0.68	0.32	0.88	0.26
(c)	0.40	0.13	0.29	0.78	0.81	0.89
W-4 (a)	1/7	0/1	1/6	3/6	24/26	52/57
(b)	0.60	0.80(1)	0.46	0.92	0.21	0.32
(c)	0.22	0.33	0.25	0.50	0.89	0.90
W-3 (a)	2/8	0/8	1/3	2/5	15/15	63/68
(b)	0.12	0.74(1)	0.65(1)	0.64	0.07	0.54
(c)	0.30	0.10	0.40	0.43	0.94	0.92
W-2 (a)	1/15	0/4	2/5	4/6	9/10	67/68
(b)	0.54(1)	0.82	0.68(1)	0.54(1)	0.75	0.30
(c)	0.11	0.17	0.43	0.63	0.83	0.93
W-1 (a)	1/15	0/5	1/5	0/0	11/11	71/73
(b)	0.54(1)	0.66	0.68	—	0.17	0.54
(c)	0.11	0.14	0.29	—	0.89	0.95

Note: item (a) lists [no. of successes/total no. of observations]. Item (b) lists the p-value pertinent to rejecting the hypothesis that q_j is the true success probability for targets in category j. In several instances (such as week W-6, $q_j = 0.2$), the number of successes matches the median value of the distribution under the null hypothesis. In such a case, the entry 0.64(1) indicates the p-value for a *one-tailed* test of the hypothesis. Item (c) lists the revised probability of success for targets in category j based on the outcomes in item (a) and given a prior on q_j which is uniformly distributed on [0, 1].

III. Concluding Remarks

In summary, the following conclusions can be drawn from an empirical analysis of the six-year sample of cash tender offers.

1. Movements in target stock prices during the offer period are informative of the success or failure of the tender (and clearly superior to base-rate forecasts). The higher the relative stock price, the greater the chance of tender success.
2. The market's probability predictions improve monotonically over time (i.e., as the conclusion date nears). Both the calibration and the resolution of forecasts improve.
3. With few exceptions, market prices are well-calibrated, i.e., the current target price during the offer period measures the expected (discounted)

to earn them occur relatively infrequently, only four times and twelve times in six years for week 1 and week −6 targets.

stock price at the conclusion date. In selected cases, it is possible that an optimal investment strategy could earn excess returns by purchasing undervalued targets. However, the opportunities for earning excess returns occur infrequently.

This study is an initial attempt to analyze the probabilistic forecasts implied by market price movements and as such carries with it important limitations. First, by necessity the results are restricted to noncompetitive tenders—those in which a single offer ends in success or failure. This restriction allows one to draw from the current target stock price an unambiguous estimate of the probability of tender success. By contrast, in competitive takeover bidding, it is common for the current stock price to rise above the initial tender offer in anticipation of (or in response to) higher competitive bids. Obviously, the present sample abstracts from the interesting dynamics of auction-like competition for the target firm.[19]

Furthermore, the limitation to noncompetitive tenders introduces a potential sampling bias. In the chosen sample, competitive offers for the target failed to appear ex post, a fact that the market could not know ex ante. Thus, one would expect a portion of the target price increase to reflect the possibility of higher competitive prices. In the absence of such bids, market prices would appear on average to be overvalued. However, the evidence from Table II (A and B) indicates that targets are generally *undervalued* during the offer period. (The main exception is the 0.95 probability category. Here, the possibility of a future competing offer greatly increases the risk of a strategy of short selling.) Thus, this potential sampling bias would not explain these cases of market miscalibration (infrequent though they are).[20]

Finally, it goes without saying that the construction of probabilistic market forecasts and their testing put heavy demands on the sample data. Beyond the usual problem of sampling variation in the actual tender outcomes, the probability estimates themselves are subject to obvious measurement errors. Margins of error attach not only to P_F but also to r_f (particularly since the precise duration of the offer period is not always known). Against the background of these statistical limitations, the information content of target price movements appears all the stronger.

[19] Because of the limitation to tenders for 100% of the outstanding stock, the present study also abstracts from partial offers made for the purpose of managerial control (see Bradley [2] on this point).

[20] An explanation for the observed absence of market bias may be the fact that only in recent years and for high-value companies have competing offers become relatively frequent. Furthermore, when the initial offer is for 100% of the shares as in our sample (and not a partial offer aimed at effective control), the likelihood of competing offers is reduced. Thus, the market's rational expectation is that no competing offer will be forthcoming.

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