Probability Weighting and Asset Prices: Evidence from Mergers and Acquisitions

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ABSTRACT

For mergers and acquisitions with a small failure probability, the average decline in target stock price if the deal fails is much larger than any increase that accompanies deal success. Probability weighting implies that the deal failure probability of such target stocks will be overweighted, leading them to be undervalued. I test whether investors are averse to holding such stocks and find strong supporting evidence. Target stocks with lower ex-ante failure probability yield positive abnormal returns, but other targets do not generate significant abnormal returns. A trading strategy that buys target stocks with low ex-ante failure probability and sells short target stocks with high ex-ante failure probability delivers around 1% abnormal return per month. These abnormal returns are not subsumed by a preference for positive skewness under traditional (expected) utility models; in fact, target stocks with lower ex-ante failure probability have lower betas, lower volatilities, and lower downside risk. I also find that profits from the strategy are significantly higher when arbitrage is more difficult.

Keywords: Mergers and acquisitions, Probability weighting, Cumulative prospect theory

JEL classification: D03, G12, G34

1. Introduction

A substantial body of experimental research -- starting with Kahneman and Tversky (1979) -- shows that decision makers tend to overweight the probability of tail events, such as winning a lottery.[1] Researchers have proposed different mechanisms to explain this "probability weighting" phenomenon. For example, some have suggested that tail events tend to be discussed disproportionately and are easier to recall (Tversky and Kahneman, 1973; Lichtenstein, Slovic, Fischhoff, Layman and Combs, 1978), and others that such events are psychologically more salient (Bordalo, Gennaioli, and Shleifer, 2012, 2013).[2]

The asset pricing implication of probability weighting is the following: it leads to overvaluation of lottery-type assets (assets with a small probability of a large upside gain as the probability of large gain will be overweighted) and undervaluation of disaster-type assets (assets with a small probability of a large downside loss as the probability of large loss will be overweighted). In this paper, I present a novel way of investigating probability weighting in the context of mergers and acquisitions (M&As), by examining the price behavior of the target stocks in the period between deal announcement and deal resolution.

In many ways, the M&A market provides an ideal setting in which to examine probability weighting. First, after deal announcement, the primary concern faced by the target company shareholders is whether or not the deal will be completed.[3]To a first approximation, this setting involves binary payoffs [(completed, not completed)]; this makes probability weighting easy to impute and interpret, is consistent with the way most experimental studies analyze probability weighting (for example, Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), and fits with the way the existing literature models

[1] For a review of this literature please see Fehr-Duda and Epper (2012).
[2] For more discussions of the psychology of tail events, see Burns, Chiu, and Wu (2010), and Barberis (2013).
[3] Other risks include the possibility of entry of competing acquirers and revisions of the offer price. Using a sample of M&As from 1981 and 1996, Baker and Savasoglu (2002) find that these risks are second order relative to deal completion risk.

probability weighting (Barberis and Huang, 2008). Second, as I show in Section 3.2, one can measure deal failure probabilities objectively -- based on deal characteristics such as the attitude of the target company and the payment method -- with relative ease and precision. At the same time, the decision probability that investors use to price target company stocks can also be imputed from the target stock prices, or equivalently, their expected future stock returns. Third, announced M&As commence and conclude in discrete and typically short intervals[4]. This clearly defines the period in which possible mispricing associated with probability weighting may arise.

Ideally, we would like to have deals when failure probability is small and deals when failure probability is close to one. However, in M&As, very few deals have failure probability close to one. Therefore, we focus on examining the asset pricing implications of small deal failure probabilities.

If investors tend to overweight tail events, as theory and experiments suggest, target company stocks should be underpriced when deal failure probability is small. Therefore, they should earn positive abnormal returns in the period from deal announcement to deal resolution. However, when deal failure probability is sufficiently large, there would be no probability over-weighting, and therefore, no abnormal returns on targets in such deals.

I test this prediction in two steps. First, I construct an empirical measure of deal failure probability using a logistic specification. I integrate the previous literature (Walkling, 1985; Samuelson and Rosenthal, 1986; Baker and Savasoglu, 2002; Bates and Lemmon, 2003; Officer, 2003; Bhagat, Dong, Hirshleifer, and Noah, 2005; Bates, Becher, and Lemmon, 2008; Baker, Pan and Wurgler, 2012) by incorporating a rich set of variables about acquirer

[4] In my sample, the mean (median) duration from deal announcement to resolution is 134 (100) days.

characteristics, target characteristics, and deal characteristics. The failure prediction model works very well out of sample in predicting actual deal outcomes. [5]

Second, I use a calendar time portfolio approach, similar to Mitchell and Pulvino (2001) and Baker and Savasoglu (2002), to analyze the target stock returns in the period between deal announcement and deal resolution. In order to focus on the deals with small failure probability and to have fairly large number of firms in each month for each portfolio, I sort all the deals into three groups based on the deal failure probability -- deals with failure probability below 10% are classified as targets with low failure probability, deals with failure probability between 10% and 20% are classified as targets with medium failure probability, and all the others are classified as targets with high failure probability.

The empirical results strongly support the prediction of probability weighting for target stocks in M&A deals. First, I find that the target stocks in deals with small deal failure probability yield around 0.80% abnormal return per month between deal announcement and resolution. Second, when I examine target stocks in deals with high deal failure probability, I find no evidence of abnormal returns. A trading strategy that buys target company stocks in deals with low failure probability and sells short target company stocks in deals with relatively higher failure probability yields an alpha of 0.75% to 2.23% per month, depending on sample selection and model specifications. I also find that, compared to the short side of the portfolio, the long side of the portfolio has a lower beta, lower downside risk, and lower coskewness as measured by Harvey and Siddique (2000), suggesting that the positive abnormal return is unlikely to be driven by systematic risk exposure. My results are robust to subsamples, subperiods, and alternative models of deal failure probability, and are stronger when arbitrage is more difficult.

[5] See Figure 3 for details.

I examine two alternative explanations. First, for mergers and acquisitions with a small failure probability, the average decline in the target stock price if the deal fails is much larger than any increase that accompanies deal success. This implies that targets in such deals have negative return skewness. Many traditional utility functions, for example, the CRRA utility function, also exhibit a preference for skewness. I thus examine whether the findings can be explained by skewness preference implied from the traditional utility function. In a stylized model with CRRA utility and under-diversification, I show that the skewness preference in traditional utility functions is not strong enough to explain my findings.

Second, Grinblatt and Han (2005), and Frazzini (2006) argue that the disposition effect can lead to excess selling after price increases, which will drive the current stock price below the fundamental value and consequently yield higher future stock returns. Typically, an M&A announcement is "good news" for the target shareholders. The disposition effect will therefore predict an under-reaction. This effect may be stronger for deals with low failure probability, as their initial price run-up is likely to be higher. In other words, in deals with low failure probability, the target price will increase more on announcement, which will mean higher capital gains for existing shareholders. The disposition effect will make these shareholders more likely to sell the stock. This might depress the stock's price, beyond fundamentals, and therefore lead to higher returns in the near future. I find that both the target return prior to deal announcement and the return around the announcement period predict the future target stock return, which is consistent with the disposition effect-based explanation outlined above. However, controlling for the pre-announcement and announcement returns does not reduce the significance of my main results.

My paper fits into a growing literature that applies probability weighting to real world phenomena. On the theory side, Barberis and Huang (2008) examine the implications of probability weighting for security prices. The existing literature testing Barberis and Huang (2008) focuses on the prediction of probability weighting that investors will prefer to buy positively skewed assets (Kumar, 2009; Mitton and Vorkink, 2007) and will be willing to pay a premium for them. Using various measures of skewness, Boyer, Mitton, and Vorkink (2010), Amaya, Christoffersen, Jacobs, and Vasquez (2013), Bali, Cakici, and Whitelaw (2011), and Conrad, Dittmar, and Ghysels (2013) document consistent evidence. Skewness preference also helps explain the first-day returns and long-run underperformance of IPOs (Green and Hwang, 2012), the prices of out-of-money options (Boyer and Vorkink, 2013), the underperformance of distressed stocks (Conrad, Kapadia, and Xing, 2013), and the underperformance of stocks trading in the over-the-counter markets (Eraker and Ready, 2011). Polkovnichenko and Zhao (2012) and Chabi-Yo and Song (2013a) find that the probability weighting function imputed from S&P 500 index options is inverse-S shaped, consistent with probability weighting. Chabi-Yo and Song (2013b) find that probability weighting has predictive power for currency returns beyond what standard disaster risk models predict. Spalt (2012) finds that probability weighting can help explain why riskier firms grant more stock options to their employees. Schneider and Spalt (2013) argue that managers tend to overpay for lottery type targets and Schneider and Spalt (2012) find that conglomerate companies overinvest in high-skewness segments.[6] My findings complement this literature by showing direct evidence of probability weighting in a context where objective probabilities are relatively easy to distinguish from decision probabilities, and

[6] Many other papers also examine probability weighting. For example, Ali (1977) and Snowberg and Wolfers (2010) document consistent evidence from racetrack betting, while Polkovnichenko (2005) uses it to explain the under-diversification of household portfolios. Brunnermeier and Parker (2005) and Brunnermeier, Gollier, and Parker (2007) endogenize probability weighting in an optimal expectation framework where the agent chooses his/her beliefs to maximize well-being.

where the binary nature of the outcome variable allows for easy interpretation of the empirical evidence.

My findings also contribute to the merger arbitrage (also called risk arbitrage) literature. After deal announcement, the target stock price is typically lower than the offer price. Merger arbitrage refers to the strategy that attempts to profit from this spread. In doing so, arbitrageurs buy the target stock, and if the offer involves stock, sell short the acquirer stock to hedge the risk induced by fluctuations in the acquirer stock price. Bhagat, Brickley, and Loewenstein (1987), Karolyi and Shannon (1999), Larcker and Lys (1987), Mitchell and Pulvino (2001), Baker and Savasoglu (2002), and Jindra and Walkling (2004) find that, on average, target stocks yield positive abnormal returns in the period between deal announcement and deal resolution. Larcker and Lys (1987) attribute the positive abnormal returns to compensation of information acquisition of the merger arbitrageurs. Baker and Savasoglu (2002), Geczy, Musto, and Reed (2002), Mitchell, Pedersen and Pulvino (2007), Mitchell and Pulvino (2001, 2012), and Officer (2007) investigate how limits to arbitrage affect the merger arbitrage market.[7] Instead of examining the target stock return unconditionally, I examine the target stock return conditional on its ex-ante deal failure probability. My findings suggest that target stock performance is related to deal failure probability, and refining merger arbitrage strategies to incorporate this finding is likely to improve profits significantly.

The rest of paper is structured as follows. In Section 2, I develop the main testable hypotheses. Section 3 describes the data and the method used to model deal failure probability. Section 4 presents the empirical results. Section 5 concludes.

[7] Giglio and Shue (2013) find that the deal success hazard rate decreases as time passes after the deal announcement, but investors do not fully take this into account when they price the target stock.

2. Hypothesis development

2.1 Probability weighting: Some background

Economists have long recognized that people are more sensitive to the probability of tail events than typical events. For example, Tversky and Kahneman (1992) find that the median subject in their experiment is indifferent between receiving a lottery with 1% chance of winning $200 and a certain $10, and also indifferent between receiving a lottery with 99% chance winning $200 and a certain $188. It is hard for the expected utility model to generate such behavior, as in that model, events are weighted linearly by their objective probabilities. To accommodate this, researchers propose probability weighting functions which transform objective probabilities into decision probabilities. Many models have incorporated this mechanism, for example, rank-dependent expected utility models (Quiggin, 1982; Yaari, 1987; Prelec, 1998) and prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). A substantial body of experimental studies show that incorporating probability weighting can more accurately describe people's decision making under uncertainty than expected utility theory (Kahneman and Tversky, 1979; Fehr-Duda and Epper, 2012).

Probability weighting can be driven by either erroneous beliefs about objective probability (probability estimation error) or by people behaving as if they knowingly assign a disproportionately higher weight to tail events (overweighting objective probability). For the former, the difference in objective probability and the decision probability reflects the error investors make in probability estimation. However, according to the latter view, the disparity between objective probability and decision probability is just a modelling device that captures investors' inherent risk preferences (Kahneman and Tversky, 1979). [8]

[8] See Barberis (2013) for more details.

Both views have received considerable attention in the psychology literature. For the probability estimation error view, the availability heuristic and anchoring bias are often cited as potential reasons why erroneous beliefs lead to overestimation of the probability of tail events. The availability heuristic predicts that, when judging the frequency or probability of an event, people tend to rely on the ease with which an example of the event comes to mind (Tversky and Kahneman, 1973). Tail events are more available as they are discussed disproportionally more than typical events and are easier to recall. For example, Lichtenstein, Slovic, Fischhoff, Layman and Combs (1978) find that people overestimate the frequency of rare but more discussed causes of death like accidents and homicide. Specifically, subjects thought that accidents caused about as many deaths as disease and that homicide was a more frequent cause of death than suicide. Actually, diseases cause about 16 times as many deaths as accidents, and suicide is twice as frequent as homicide.

Anchoring bias may also be a source of probability weighting. Event space is usually specified into coarse categories. Fox and Clemen (2005) and Sonnemann, Camerer, Fox and Langer (2013) find that a typical subject in the experiment tends to assign equal probability to the specified events. For example, we may classify market conditions as up market, down market and flat market. Experimental subjects tend to assign the same probability to each specified event. For this example, subjects tend to assign 1/3 to up market, down market and flat market, even when their true probabilities are different. Fox and Clemen (2005) and Sonnermann, et al. (2013) do find subjects tend to make adjustment to the correct direction, however, they anchor to the equal assignment and adjust insufficiently. In reality, normal events in the middle of a distribution are typically partitioned more coarsely than events that lie at the extremes of a distribution. As a result, the objective probability of a specified tail event is typically lower than a specified normal event. Equal probability assignment and anchoring therefore predicts overweighting of tail events.

Many mechanisms have also been proposed to explain the second view of probability weighting – that people behave as if they intentionally put higher weight on tail events. For example, Rottenstreich and Hsee (2001) propose that tail events can make people more emotional. Recently, Bordalo, Gennaioli, and Shleifer (2012) propose a salience-based theory of choice under uncertainty. The psychology literature documents that salience attracts attention. For example, according to Kahneman (2011, p324), "our mind has a useful capability to focus on whatever is odd, different or unusual." Based on this, Bordalo et al. (2012) argue that decision makers' attention is likely to be drawn to salient outcomes, such as extreme tail outcomes, which leads to overweighting of these outcomes.

2.2 Probability weighting in merger and acquisition deals

There are multiple reasons why probability weighting may matter in M&As. For an M&A deal that involves a small deal failure probability, the target stock price is typically close to the offer price. If the deal succeeds, which happens with a high probability, by definition, the stock price will only increase for a small amount up to the offer price. But in the unlikely event that the deal fails, the stock price will drop by a much larger amount. If investors recall the large losses suffered on previous deal failure disproportionately (availability heuristic), investors may overestimate the true probability of deal failure. Alternatively, it is also possible that they do not make systematic errors in judging the probability itself, and that it is an inherent aversion to large, small-probability losses that results a lower willingness-to-pay for deals with small failure probabilities (Rottenstreich and Hsee, 2001; Kahneman and Tversky, 1979; Bordalo, Gennaioli, and Shleifer, 2012). Although a distinguishing between the two alternatives is beyond the scope of this paper, I will provide some indicative evidence in Section 4.8.

2.3 Asset prices with probability weighting

Several models have been proposed to analyze the asset pricing implication of probability weighting. Barberis and Huang (2008) consider an economy in which investors have cumulative prospect theory preference, and examine how a lottery-type security – a security with a small probability of large gain and a large probability of small loss – is priced in a mean-variance world. They show that, in such an economy, lottery-type securities can become overpriced and earn negative abnormal returns.

Barberis, Mukherjee, and Wang (2013) also model probability weighting using cumulative prospect theory. But different from Barberis and Huang (2008) in which investors make decisions at the portfolio level, Barberis, Mukherjee, and Wang (2013) assume that investors derive their prospect theory preference from individual stocks (i.e., engage in narrow framing). Similarly, Bordalo, Gennaioli, and Shleifer (2013) also assume investors engage in narrow framing, but they model probability weighting based on the salience of a payoff. In contrast to rank-dependent utility and cumulative prospect theory where probability weighting function is constant, in Bordalo, Gennaioli, and Shleifer (2013), probability weighting function is context dependent: it relies on other alternatives and how a decision problem is described. Brunnermeier and Parker (2005) and Brunnermeier, Gollier, and Parker (2007) endogenize probability weighting in an optimal expectation framework where the agent chooses his/her beliefs to maximize well-being. Though the mechanisms are different, all these models predict that lottery-type securities can become overpriced and disaster-type securities (securities with a small probability of large loss and a large probability of small gain) can become underpriced.

To illustrate the central point of probability weighting, I use a simple model to show the link between deal failure probability and the expected target stock return, and to develop the hypothesis. In the model, the deal will either fail or succeed. If the deal succeeds, the target shareholder receives the offer price P_{offer}. If the deal fails, the target is worth its standalone value P_{alone}, where I assume that $P_{offer}>P_{alone}$. P_{offer} and P_{alone} are assumed to be constant and known[9]. The deal failure probability is π where $0< \pi <1$. The post-announcement target stock price is denoted as P; it is determined by P_{offer}, P_{alone}, π, and the utility function of investors. For simplicity, I also assume that investors are risk neutral and that the risk-free rate is normalized to 0. Figure 1 shows the setting graphically.

[Insert Figure 1 here]

When investors are risk neutral, traditional expected utility theory predicts that the post-announcement target stock price is equal to its expected payoff, that is:

$$P = \pi P_{alone}+(1-\pi)P_{offer}. \tag{1}$$

However, in Part I of the Appendix, I prove that, in theories with probability weighting, we have:

$$P=w(\pi)\ P_{alone}+(1-w(\pi))\ P_{offer}, \tag{2}$$

where $w(\pi)$ is the relative decision weight investors put for deal failure. Generally, $w(\pi)>\pi$ when π is small and $w(\pi)<=\pi$ when π is moderate or large. With probability weighting, the expected return of the target is:

$$[\pi P_{alone}+(1-\pi)\ P_{offer}]/[w(\pi)\ P_{alone}+(1-w(\pi))\ P_{offer}]-1. \tag{3}$$

It is easy to show that this is positive if $w(\pi)>\pi$ and (weakly) negative if $w(\pi)<=\pi$. This leads to the the main hypothesis of this paper:

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[9] In reality, competitors may join in the bidding; the offer price is also subject to revision; if the payment is not pure cash, the target shareholders may not know exactly what P_{offer} will be; being targeted will also reveal a lot of valuable information to the market and potentially change the strategy of the target management even if the deal fails, which will also change the target value. All these make P_{offer} and P_{alone} variable. However, as long as the market has a reasonable estimation of P_{offer} and P_{alone}, and their variances are low comparing to their difference, the model is a good approximation of reality.

Hypothesis: Target stocks in deals with low failure probability yield positive abnormal returns; target stocks in deals with relatively high failure probability yield no significant abnormal returns or negative abnormal returns.

One remaining questions is: what is the range of $\{\pi | w(\pi)>\pi\}$, in other words, when will π be overweighted? Different probability weighting functions have different answers to this question, but most predict that the fixed point (when $w(\pi)=\pi$) is around 0.3 (Tversky and Kahneman, 1992; Prelec, 1998). If investors ignore diversification, we predict that targets will be undervalued when deal failure probability is lower than 0.3. However, this may not be the case in the financial markets. First, the average investor may be different from the average experimental subject, given the presence of many sophisticated institutions. Second, not all investors engage narrow framing and they may make decisions by incorporating the effect of π in their overall portfolio. The negative skewness driven by small π may be partially diversified in a portfolio and the pricing effect of probability weighting may become weaker. Ultimately, the range of π for which targets will be undervalued is an empirical question.

3. Data and modeling deal failure probability

3.1 Data

I begin with all the M&As in the Securities Data Company database of Thompson Financial (SDC). SDC covers deals going back to 1978. However, coverage prior to 1981 is incomplete. The sample used in this paper runs from January 1, 1981 to December 31, 2010. After I use the following filters, I am left with a sample of 16,906 deals after I use the following filters:

1. The target is a U.S. listed firm.
2. The deals that are classified by SDC as rumors, recapitalizations, repurchases, or spinoffs are excluded.

3. In order to calculate target characteristics and post announcement return, I also require that the price and return data are available from Center for Research on Security Prices (CRSP) one year prior to deal announcement and at least three trading days after deal announcement.
4. The deal completion or date of withdrawal must be at least three days after the deal announcement, or missing.

Table 1 shows the sample of deals. The number of deals is large in late 1980s and 1990s. The deal duration is measured as the number of calendar days between deal announcement and deal completion or withdrawal. The median duration is 100 days and the mean is 134, suggesting that the deal duration is right skewed. 1,144 deals are initially viewed as hostile or unsolicited by the targets.[10] Payment method data shows that the number of pure stock deals is highest during the internet bubble. Around 21.2% of the deals are conducted through tender offers. Leverage Buyouts (LBO) and mergers of equals (MOE) are generally rare. Only 6.6% and 0.8% are LBOs and MOEs, respectively. 55.5% of the acquirers are public firms. Past return is the cumulative return from 365 days to 22 trading days prior to deal announcement. The variation is large, but on average, the target past return is 9.65%, close to the market return. Target Size is the natural logarithm of target firm market capitalization 22 trading days prior to deal announcement. I convert market size into constant 2005 dollars using the GDP deflator from the Federal Reserve. Mean target size is relatively stable in the early years, begins to increase only in 2004 and reaches a peak in 2007.

[10] As the ultimate purpose of this paper is to do asset pricing tests, it is important to make sure that all the information used to construct portfolios is available at the moment of portfolio construction. Thus, I choose to use the initial attitude of the target company to the merger and acquisition announcement, instead of the final attitude.

Prior Bid is a dummy variable which is equal to 1 if the target company has received another takeover bid in the past 365 days. The results show that, for 24.6% of the deals, another bid was received in the past 365 days. The data also reveals significant variation in geographical and industrial linkage between the acquirer and the target: for 15.4% of the deals, the acquirers are foreign firms; for 26.7% of the deals, the acquirer and the target are not located in the same state; and for 43.7% of the deals, they are not in the same 2-digit SIC industry.

[Insert Table 1 here]

I also look at acquirers' pre-acquisition ownership of target companies in these deals. Pct Held is the percentage of the target shares held by the acquirer 6 months prior to the deal announcement. Toehold is a dummy which is equal to 1 if the holding is no less than 5%. Cleanup is a dummy variable which is equal to 1 if the holding is greater than 50%. Around 3.4% of the deals are cleanup deals. The acquiring firm has a toehold only in 14.3% of the deals. But on average the acquirers hold 4.41% of the target shares, close to the cutoff used to define toehold. This implies that once an acquiring firm holds shares of the target firm, it is very likely that it holds a significant fraction.

In the whole sample, 10,692 deals are completed, and 3,167 are withdrawn. Most of the remaining deals are classified as pending or status unknown by SDC. Based on the deals with known status, the average completion rate is 77.1% (10,692/(10,692+3,167)). As the pending and status unknown cases may be different from the cases with known status, in order to prevent any sample selection bias, I include all of them in my asset pricing tests, but in modeling the deal success probability, I only use the deals with known status. In the next section, I discuss in detail how I model deal failure probability.

3.2 Modeling deal failure probability

I use two models to estimate deal failure probability. The first is based on deal characteristics; the second is based on the target stock price. I refer to the first model as the characteristics-based model, and to the second as the target price-based model. Throughout the analysis, I use π to denote deal failure probability.

3.2.1 The characteristics-based model

Following the literature (Walkling, 1985; Samuelson and Rosenthal, 1986; Baker and Savasoglu, 2002; Bates and Lemmon, 2003; Officer, 2003; Bhagat, Dong, Hirshleifer, and Noah, 2005; Bates, Becher, and Lemmon, 2008; Baker, Pan and Wurgler, 2012), I use deal characteristics and firm characteristics in a logistic specification to predict deal outcome.

The deal and firm characteristics that I use are: a hostile dummy variable to measure the target attitude (Baker and Savasoglu, 2002; Baker, Pan, and Wurgler, 2012), a pure cash dummy variable and a pure stock dummy variable to measure the payment method (Bates and Lemmon, 2003; and Bates, Becher, and Lemmon, 2008), a Tender dummy variable, an LBO dummy variable and a merger of equals (MOE) dummy variable to measure the deal type. Following Officer (2003), I put three variables—Pct Held, Toehold, and Cleanup—in the model to capture the effect of the acquirer's pre-acquisition ownership. Toehold is a dummy variable which is equal to 1 if the holding is no less than 5%. Cleanup is a dummy variable which is equal to 1 if the holding is greater than 50%. I also consider acquirer and target characteristics such as the public status of the acquirer, and the size and past return of the target. Other factors include dummy variables indicating whether the target received any takeover offer in the past 365 days (Prior Bid), whether the acquirer is a foreign company, and whether the acquirer and the target are from the same state or in the same 2-digit SIC industry. Prior Bid accounts the competitiveness of the takeover market and the other variables account for the possible effect of geographical and economic linkages between the two sides of the deal.[11]

[Insert Table 2 here]

Table 2 reports the results. The dependent variable is a dummy variable which is equal to 1 if the deal is withdrawn, and 0 if the deal is completed. Models (1) to (6) report the coefficients and the second column of model (6) reports the marginal effects based on model (6).[12] In estimating the model parameters, I only use the deals with known status in the sample.

I first examine five sets of factors separately and in model (6) I examine all the factors in one full model. Almost all the factors considered have significant predictive power for the deal outcome and the estimated signs are very similar in the separate models and in the full model. The results in the model (6) show that the significantly positive predictors include hostile, LBO, MOE, Toehold, Cleanup, Prior Bid, and Cross Border. The negatively significant variables include Pure Cash, Pure Stock, Tender, Pct Held, Public Acquirer, Target Past Return, Target Size, and Same Industry. The only variable that is insignificant in model (6) is the Same State dummy. By examining the marginal effects reported in the last column, we can compare the importance of the various predictors. Among all the dummy variables, five have an absolute average marginal effect larger than

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[11] The literature has also uncovered other important determinants of the deal outcome. For example, Bates and Lemmon (2003) and Officer (2003) find that target and bidder termination fees act as an efficient contract mechanism to encourage bidder participation and to secure target company gain, and increase the deal completion rate. Burch (2001) and Bates and Lemmon (2003) find that lockup options also increases the deal completion rate. Officer (2004) argues that collar provisions can be used as contractual devices by lowering the costs of target and acquirer renegotiation. I do not consider these contractual terms because they may not be available to the public at the beginning of the deal. Considering these factors has little effect on the main results.

[12] For most variables, the marginal effects in models (1) to (5) are similar to those in model (6). To save space, I do not report the marginal effects for models (1) to (5).

0.100. They are: hostile (0.565), LBO (0.146), Prior Bid (0.142), Tender (-0.118), and Toehold (0.106).

Next, I examine the predictive performance of my method of assessing deal failure probabilities in real time. In order to avoid any look-ahead bias, I use an out-of-sample estimation method similar to Campbell, Hilscher, and Szilagyi (2008) to estimate out-of-sample deal failure probability. Specifically, for the deals in year t, I use all the data before year t to estimate the model coefficients. Only deals that have already been completed or withdrawn by the end of year t-1 are included in the estimation.[13] The estimated coefficients are used to calculate the deal failure probability for all the deals in year t, including the deals with status classified as pending or unknown by SDC.

In order to have robust coefficient estimate, I require at least three years data to do the estimation. Thus, the main test sample begins in 1984 and ends in 2010; 16,163 deals are used in the asset pricing tests.

[Insert Figure 2 here]

Figure 2 shows the distribution of the deal failure probability when using model (6). I classify the deals into 100 groups based on their failure probability. The vertical axis shows the number of deals in each group. It shows that deal failure probability has large variation. Deals with failure probability higher than 50% are generally rare, while a large number of deals have failure probability lower than 10%. Overall, the distribution of deal failure probabilities is fairly smooth.

[Insert Figure 3 here]

In order to examine whether the model in Table 2 does a good job in predicting deal outcomes, I sort all the deals into 100 equal-sized bins according to their predicted failure

[13] This means that the deals that are announced before or in year t-1 but have not been completed or withdrawn at the end of year t-1 are not used.

probability using model (6) in Table 2. The x-axis is the average predicted failure probability and the y-axis is the realized failure rate. Realized failure rate is calculated as: Number of deals withdrawn / (Number of deals withdrawn + Number of deals completed).

As the first half the sample period is dominated by hostile takeovers, besides reporting the results for the whole sample period from 1984 to 2010 (Panel A of Figure 3), I also report results for two sub-periods (Panels B and C of Figure 3). As shown in the figure, the forecasted failure probability is a good predictor of realized failure-- both in the whole sample period, as well as in the two sub-periods. I also run a simple OLS model with the realized failure rate as the dependent variable and the predicted failure probability as the independent variable. The results are also shown in the three panels. For the whole sample period, 1984-1996, and 1997-2010, the coefficients of the fitted failure probability are all around 0.6-0.7, all of which are highly statistically significant. The R^2 for the whole sample period is 0.790, suggesting that the deal failure probability model predict actual outcomes very well.

[Insert Figure 4 here]

In Figure 4, I examine whether the model in Table 2 does a good job in predicting deal outcomes, year by year. I sort all the deals into three groups: low failure probability group (deals with failure probability lower than 10%), medium failure probability group (deals with failure probability between 10% and 20%), and high failure probability group (all the others).[14] I calculate the realized deal failure rate for each group and each year. Panel B of Figure 3 shows that the deals with low failure probability indeed have a lower realized failure rate than the deals with high failure probability, consistent with Figure 3, but

[14] I choose 10% and 20% as the cut-offs mainly because I will do the asset pricing analysis using the same grouping.

perhaps more pointedly, this is true in each and every year in my sample. The deals with medium failure probability also lie in between the two extreme groups in most years.

In addition, the model does a better job in the second half of the sample than in the first half. For example, the model fit (both R^2 and the coefficient of Fitted) is worse in the first sub-period (Panel B of Figure 3) than in the second sub-period (Panel C of Figure 3). In Figure 4, in the 1980s, though deals with different failure probability are clearly separated, the realized failure rate is higher than the fitted failure probability. I conjecture that this is driven by the hostile takeovers in late 1980s. But overall, the results show that the model in Table 2 has very good out-of-sample predictive power in separating deals with different failure probabilities.

3.2.2 The target price-based model

Another way of modeling deal failure probability is to infer it by comparing the offer price and the post-announcement target price. Consider the example in Figure 1: if we know the offer price (P_{offer}), the target standalone price (P_{alone}) and the post-announcement target price (P), it is easy to infer how the market perceives the likelihood of deal failure. I use the following formula as my second measure of deal failure probability: $(P_{offer} - P)/(P_{offer} - P_{alone})$. Strictly speaking, the target price is not only affected by its standalone price, the offer price, and the failure probability. It is also affected by the expected length of time needed to resolve the deal and thus the expected return required to hold the target until then. However, regardless of the exact asset pricing model, I expect that $(P_{offer} - P)/(P_{offer} - P_{alone})$ should be positively related to deal failure probability.

To prevent any look-ahead bias, I use the initial offer price (instead of the final offer price) to do the calculation. I use the target price 22 trading days before the deal announcement to proxy target standalone value. The post-announcement target price is measured at the end of the second trading day after deal announcement. In order to minimize measurement error, I require that the post-announcement target price is between the pre-announcement target price and the offer price.[15] 4,598 deals remain.

In model (7) of Table 2, I analyze the predictive power of the price-based measure for the deal outcome. The results show that $(P_{offer}\text{ -}P)/(P_{offer}\text{ -}P_{alone})$ has very strong predictive power for the deal outcome. The coefficient of $(P_{offer}\text{ -}P)/(P_{offer}\text{ -}P_{alone})$ is 2.195, the t-value is 15.70, and the marginal effect is 0.319, suggesting that an increase of 0.1 in the value of $(P_{offer}\text{ -}P)/(P_{offer}\text{ -}P_{alone})$ increases the failure probability by 3.19%. This is consistent with the findings of Samuelson and Rosenthal (1986) and Subramanian (2004) that the market can extract deal failure probability very well even at the beginning of a deal.

Compared to the deal characteristics-based measure, this price-based measure is simpler. However, due to the constraint on the initial offer price in calculating $(P_{offer}\text{ -}P)/(P_{offer}\text{ -}P_{alone})$, it is only available for less than 30% of the full sample and is very sparse in the years before 1996. Thus, in the paper, I use the characteristics-based measure as my main measure and perform robustness tests using the price-based measure.[16]

4. Empirical results

In this section, I evaluate the average return of target firms after the deal announcement and test whether investors overweight probability of deal failure when it is small. In order to have fairly large number of firms in each month for each portfolio, I sort all the deals into three groups based on the deal failure probability. The deals with failure

[15] Both the offer price and the target standalone price are measured with noise. Competitor entry or expectation of competitor entry can drive the post-announcement target price higher than the first offer price. It is also possible that some extremely good or bad news comes out during the month just before the deal announcement and takes the post-announcement target trading price beyond the range bounded by the pre-announcement and the offer price.

[16] Both models are likely to have some error-in-variable problems. For example, for the characteristics based model, it is possible that investors may use other available information which may have significant effect on deal failure. For the priced-based model, I do not consider the heterogeneity in deal duration. Given the error-in-variable problem, I expect that my results may underestimate the true importance of probability weighting.

probability below 10% are classified as targets with low failure probability, the deals with failure probability between 10% and 20% are classified as targets with medium failure probability, and all the others are classified as targets with high failure probability.

I classify in this way for two reasons. First, probability weighting has its biggest impact on tail events, I therefore define deals with low failure probability as deals with a very low chance of failure. Second, the number of deals with failure probability higher than 20% is more volatile year by year. If I do a finer classification, the number of deals in some categories will be too small. For example, if I classify deals with failure probability higher than 20% into 3 categories-- between 20% and 30%, between 30 and 40%, and others-- for some months, the number of deals will be as low as 1. This problem will become more severe for the subsample analysis in Table 5. Nevertheless, my results are robust if I further sort deals with high failure probability into 3 categories: between 20% and 30%, between 30 and 40%, and others.

4.1 Target company characteristics

In Table 3, I report the characteristics of target stocks. Panel A reports all characteristics except for the target stocks' return moments, and Panel B reports their return moments. The first column of Panel A shows the average deal failure probability for each group. Not surprisingly, the averages are 0.052, 0.154, and 0.362 for Low, Medium and High, respectively. The difference between Low and High is 0.310, which is economically quite large. The next two columns show the mean and median durations of deals in each group. The mean (median) durations are 100.87 (62), 137.44 (113), and 142.94 (107) for Low, Medium, and High, respectively. I use the standard two sample t-test to examine the statistical significance of the mean and the Brown and Mood (1951) test to examine the statistical significance of the median. The differences in mean and median between the Low and High groups are both statistically significant, suggesting that deals with low failure probability on average resolve faster than other deals. The last column shows the average premium. Premium is measured as the natural log difference between the initial offer price and the target stock price 22 trading days before deal announcement. The average premia are 0.353, 0.354 and 0.382 for Low, Medium and High, respectively. The difference between Low and High is not statistically significant.

Panel B reports the target stock return moments. I use two methods to calculate the characteristics of target stocks: one based on the realized return (physical moments) and one based on option prices (risk neutral moments). For risk neutral moments, I can calculate the moments stock by stock, as long as there is a large enough number of options available. I follow Bakshi, Kapadia, and Madan (2003) and Dennis and Mayhew (2002) to calculate the risk neutral moments.[17] However, I cannot calculate the physical moments for each individual stock as there is only one realized return for each of them. I thus calculate the physical moments from the cross section of target stocks. Specifically, I calculate the cross-sectional moments for stocks in the three portfolios. To mitigate the effect of extreme returns, I calculate the physical moments from log returns rather than raw returns.

[Insert Table 3 here]

As shown in Figure 1, the payoff structure of the target stock is (approximately) binary. If this is true, the statistical moments of target stock returns should reflect the characteristics of the Bernoulli distribution. The standard deviation and skewness for a Bernoulli distribution are $\pi(1-\pi)$ and $(1-2\pi)/[\pi(1-\pi)]^{1/2}$, respectively. Standard deviation increases with respect to deal failure probability when failure probability is lower than 0.5 (which is true for most of the sample stocks), and skewness is negatively related to deal

[17] The detailed methodology can be found in Part II of the Appendix.

failure probability (in other words, skewness is more negative when deal failure probability becomes smaller).

The results in Table 3 support these predictions about standard deviation and skewness. From Table 3, I find that the standard deviation of the target stock return is highest for stocks with high failure probability. For the target stock with low failure probability, its return standard deviation is 21.6%, but the return standard deviation of target stocks with high failure probability is 38.9%, almost double that of the low failure probability group. From Low to High, the cross sectional skewness increases from -3.249 to -2.043.

The risk-neutral measures, calculated from option prices, show similar results for all the three moments, though the number of stocks for which I can calculate risk neutral moments is significantly smaller, as target companies on average are small stocks and may not have traded options. However, in total, I still have more than 1,000 target stocks for which I can calculate risk neutral moments. Furthermore, the results show that the differences in standard deviation and skewness between the high- and low-failure probability groups are both significantly different from zero.[18] Overall, both the results of comparing standard deviation and skewness are consistent with targets having a payoff structure that is approximately binary.

4.2 Details of the calendar portfolio construction

Following Mitchell and Pulvino (2001) and Baker and Savasoglu (2002), I use calendar time portfolios to test the asset-pricing implications of probability weighting. Upon an announcement of an M&A, the deal is classified into one of the three categories (deals with low/medium/high failure probability) based on its failure probability. I begin to include a target stock into one of the three portfolios from the end of the second day after

[18] To mitigate the effect of extreme values in the statistical test, in unreported results, I also perform a Wilcoxon rank test. The results are robust.

the deal announcement. This is to exclude the large abnormal returns that are associated with deal announcement. The holding period ends when the time to announcement exceeds 180 days or when the deal is completed or withdrawn, whichever comes first. To mitigate the bias of using daily equally weighted returns to calculate compounded monthly returns (Blume and Stambaugh, 1983; Roll, 1983; Canina, Michaely, Thaler, and Womack, 1998), throughout this paper, I measure all portfolio returns using value weights, where the weight is the market capitalization of the target firm at the end of the previous day.

I compound daily portfolio returns to get the monthly return. The median number of target firms for Low, Medium, and High failure portfolios is 28, 58 and 121, respectively. This suggests that the number of stocks in each portfolio is generally not very thin, and my results are unlikely to be driven by some months with a sparse number of deals.[19]

4.3 Portfolio returns

This section reports the main results of this paper: the average returns of the Low, Medium, and High portfolios, their risks and alphas. Besides the three portfolios, I also report the characteristics of a zero-investment long-short portfolio which is the difference between Low and High.

[Insert Table 4 here]

Table 4 reports the characteristics of these portfolios. The results show that the average excess return decreases with deal failure probability, from 1.170% for the Low portfolio to 0.377% for the High portfolio.

The annualized portfolio standard deviation increases with deal failure probability, from 16.7% for the Low portfolio to 22.6% for the High portfolio. As a result, the Sharpe

[19] Out of the 324 months I have, there are 6 months in which the High portfolio has less than 10 stocks (minimum is 6), 3 months in which Low has less than 10 stocks (minimum is 8), and in all months Medium has more than 10 stocks. My results are robust if I exclude those months or if I replace return observations for those month by the risk free rate.

ratio decreases from 1.106 to 0.393. Among all the three portfolios, only Low is positively skewed, and the portfolio skewness decreases from Low to High. This is opposite to the relationship between deal failure probability and the individual stock return moments shown in Table 3, suggesting that aggregation of stocks into portfolios can change skewness significantly.[20] The relationship between deal failure probability and portfolio skewness thus suggest that, compared to the High portfolio, the Low portfolio is less likely to have an extremely low return. The mean of the Low-High portfolio is 0.793% which is economically large, and is significant at the 5% level.

The results in Table 4 are consistent with our Hypothesis. Next, I investigate whether the difference in excess return between Low and High can be explained by systematic risk exposures.

I report factor adjusted portfolio alphas in Table 5. The market model adjusted alphas are 0.808%, 0.008%, and -0.198% for Low, Medium, and High, respectively. Betas for the three portfolios are 0.633, 0.851, and 1.007, respectively. The beta for the Low-High portfolio is -0.374, which is significantly negative.

[Insert Table 5 here]

The alpha of the Low portfolio is significantly positive, while the other two are not significantly different from zero. The market-adjusted alpha for the Low-High portfolio is 1.006%, which is significant at the 1% level. The market-adjusted alpha is also higher than the difference in excess return reported in Table 3. This is because the long side has lower beta than the short side. Adjusting for the three Fama and French (1993) factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor (I will refer to this as five-factor adjustment) does not change the results significantly. The

[20] A similar finding is that the aggregate market displays negative skewness, but on average individual stock returns display positive skewness (see Albuquerque (2012) for an interpretation).

five-factor alphas for the Low, Medium, High and the Low-High portfolio are 0.766%, -0.038%, -0.293%, and 1.060%, respectively.

[Insert Figure 5 here]

Mitchell and Pulvino (2001) find that, on average, deals are more likely to fail in down markets. They suggest using non-linear asset pricing models for the risk performance analysis. In Figure 5, I show the cumulative return of the Low-High portfolio graphically. In order to compare, I also show the CRSP value weighted index. The negative relationship between market return and Low-High return is very clear in the figure. For example, during the 2007-2009 financial crisis, the market decreases by around 50%, but the Low-High portfolio increases by around 200%.[21] The results in Figure 5 suggest that the positive alpha of the Low-High portfolio is unlikely to be explained by downside risk.

To formally examine the downside risk of the Low-High portfolio, I follow Mitchell and Pulvino (2001) and use a piecewise linear regression model:

$$R_{portfolio,t}-R_f=(1-UP_t)[a_{low}+\beta_{low}(R_{m,t}-R_f)]+UP_t[a_{high}+\beta_{high}(R_{m,t}-R_f)]+\beta' X_t+\varepsilon_t$$

$$\text{subject to: } a_{low}+\beta_{low}(Threshold)=a_{high}+\beta_{high}(Threshold) \quad (4)$$

where $R_{portfolio,t}$ is the monthly Low-High portfolio return, $R_{m,t}$ is the value weighted market return, R_f is the risk free interest rate, and UP_t is a dummy variable which is equal to 1 when the market excess return is greater than a threshold. X represents the other factors. The second equation shown above ensures continuity.

[21] Though the return for the Low-High portfolio is particularly high during crisis period, the positive abnormal return of the Low-High portfolio is not a crisis only phenomenon. Specifically, I find that the alpha of the 5-factor alpha of the Low-High portfolio is 0.788% if I drop the 7 months where the CRSP excess return has a monthly return lower than -10%. Furthermore, in Section 4.5, I find that the results are robust even in the first half of the sample period (1984-1996) which does not include the two crisis periods (internet bubble crash and 2007-2009 subprime crisis).

Another way to evaluate downside risk is to examine the coskewness of a portfolio. Thus, I also examine whether the Low-High portfolio has exposure to the coskewness risk mimicking factor proposed by Harvey and Siddique (2000). Coskewness is measured as:

$$\widehat{\beta}_i = \frac{E[\varepsilon_{i,t} R^2_{m,t}]}{\sqrt{E[\varepsilon^2_{i,t}]} E[R^2_{m,t}]} \tag{5}$$

where $\varepsilon_{i,t}=R_{i,t} - a_i - \beta_i R_{m,t}$. $R_{i,t}$ and $R_{m,t}$ are the excess return for stock *i* and the excess return for the market. In each month, all the stocks in NYSE/AMEX/NASDAQ are sorted into three portfolios based on the value of coskewness which is estimated based on monthly data of the past 5 years. The 30% of stocks with the most negative coskewness is classified into an S^- portfolio and the 30% of stocks with the most positive coskewness in each month is classified into an S^+ portfolio. Both S^- - S^+ and S^- - R_f will be used as the coskewness hedging portfolios for the portfolio abnormal return analysis.

Table 6 reports the results. Panel A reports the downside risk analysis using the method proposed by Mitchell and Pulvino (2001) and Panel B reports the coskewness risk analysis. Panel A shows that both the upside beta and the downside beta are significantly negative, but the downside beta is much larger in magnitude. The difference between the upside beta and the downside beta is significant at 1% level. Panel B shows that Low-High portfolio has negative exposure on the two coskewness factors. The coskewness loading on Low-High portfolio is -0.411 and -0.294 when S^- - S^+ and S^- - R_f are used to construct the mimicking portfolio, respectively. In sum, the results show that there is less downside risk for deals that are less likely to fail.

[Insert Table 6 here]

The results in Table 5 and Table 6 show that Low-High portfolio has negative beta and negative downside risk. This is consistent with Bhagat, Brickley, and Loewenstein (1987), who view acquirer offers as put options to target shareholders. Bhagat, Brickley, and Loewenstein (1987) argue that an offer from an acquirer is similar to a put option with the strike price as the offer price and target standalone value as the underlying. Put options help hedge the risk resulted from the fluctuation of the target value. As the exercisability of put options is contingent on the deal going through, the effectiveness of hedging is determined by the probability of deal failure. The lower the deal failure probability, the better is the hedging value of the put option. Thus, the Low-High portfolio is essentially a long position in these contingent put options. If the average target stock has positive beta, on average, the price of put options will increase when market is going down (negative beta), and the price of put options increases more quickly in the down market than price decreases in the up market (negative downside risk), due to increasing option delta.

Overall, the results in Tables 4, 5 and 6 confirm the prediction of probability weighting. That is, the target stocks in deals with low failure probability are undervalued, but target stocks in other deals do not show significant mispricing, suggesting that deal failure probability is only overweighed when it is small. The long-short portfolio has negative beta and negative downside risk, suggesting that the abnormal return of the low failure probability portfolio is unlikely to be driven by exposure to systematic risk. Overall, this supports my Hypothesis.

4.4 The magnitude of overweighting

In this section, I examine the economic magnitude of overweighting for an average deal in the Low portfolio. Based on the structure assumed in Figure 1, by definition, the target stock return is equal to the expected payoff divided by the current target trading price:

$$(1+R_f+ER+AR)^{T-t}=\frac{P_{alone}*\pi+P_{alone}*(1+premium)*(1-\pi)}{P}$$

(6)

where R_f is the risk free rate, *ER* is expected return, *AR* is abnormal return, *T-t* is the length of time from deal announcement to deal resolution, P_{alone} is target standalone price, *P* is the post announcement target trading price, and π is deal failure probability. For investors who overweight the small deal failure probability, *P* satisfies the following equation:

$$P=\frac{[P_{alone}*w(\pi)+P_{alone}*(1+premium)*(1-w(\pi))]}{(1+R_f+ER)^{T-t}}$$

(7)

where $w(\pi)$ is the decision probability. Combining equation (6) and (7), we can infer $w(\pi)$ from the data.

As shown in Table 3, the average deal failure probability (π) is 5.2%., the average duration (*T-t*) is 100.87 days or 3.32 months (100.87/ (365/12)) and the average premium (*premium*) is 42.3% (exp(0.353)-1). As shown in Table 4, the average abnormal return (five factor alpha) for the Low portfolio is 0.766% per month (*AR*). The average excess return is 1.170% (Table 4) and the five-factor alpha is 0.766%. So the average "normal" excess return per month is 0.404% (*ER*). The average risk free rate from 1984 to 2010 is 0.364% per month (R_f). With these statistics, $w(\pi)$ equals 0.132%. The 90 percent confidence interval of *AR* is from 0.343% to 1.189%. Under this range, $w(\pi)$ is estimated to be from 8.8% to 17.5%.

This seems large. However, it is consistent with the experimental studies. For example, based on the probability weighting function proposed by Tversky and Kahneman (1992), 5.2% should be overweighted as 11.42%, which is quite close to the above estimates.

4.5 Robustness

Several robustness tests are presented in Table 7. The five-factor adjusted performance of the Low-High portfolio is reported. The five-factor alpha of pure cash offers is 0.748%, which is statistically significant. I also report results for the subsample of deals that involves change of corporate control. Change of corporate control is defined as deals in which the acquirer owns less than 50% of the target but seeks to own more than 50%. This subsample includes 10,353 deals. The Low-High abnormal return of this subsample is 1.058%, which is both economically and statistically significant. I also examine the first offers separately. First offers are the targets that did not receive any acquirer offers in the past 365 days. This eliminates the possibility the portfolios contains more than one position in a single target company. The Low-High portfolio alpha is 0.930%, which is similar to the whole sample results.

In Panel B of Table 7, I report the five-factor alpha of the Low-High portfolio for two subperiods. The first subperiod is from 1984 to 1996 and the second is from 1997 to 2010. Alphas are 0.763% and 2.115%, respectively, and both are significantly positive. The result for the first subperiod is weaker than the second subperiod. This is perhaps due to the predicted failure probability performing slightly worse in the first half of the sample period (as shown in Figures 3 and 4).

In the main analysis, I use a holding period that starts from the third day after deal announcement and extends 180 days after deal announcement, or until the deal is completed or withdrawn, whichever comes first. However, the length of the holding period is arbitrary. In Panel B, I report the results for alternative holding periods: 30 days, 60 days, 100 days, and 365 days. The abnormal returns from these four models are around 0.960-2.226% and are all statistically significant. Interestingly, the abnormal return decreases when the holding period increases. I conjecture that this may be because the risk of deal failure is mainly concentrated in the first two months after deal announcement.

[Insert Table 7 here]

In Panel D, I report the five-factor alpha of the Low-High portfolio using the price-based deal failure probability estimate. The alpha and beta are 1.040% and -0.598. These are similar in magnitude to those calculated using the characteristics-based deal failure probability measure, confirming my earlier findings.

Next, I attempt to carefully account for two issues that can potentially affect my conclusions. First, the structure shown in Figure 1 is a simplified version of the real world. In reality, competitors may join in bidding and the offer price may be subject to revisions. I gauge the economic importance of revisions following Baker and Savasoglu (2002). The data on offer price revisions is more complete since 1997. I thus focus on the later sample period.[22] First, I tabulate the frequency of revisions for the three portfolios of targets in my sample. From 1997 to 2010, I have 7,205 deals in total, of which 717 have their offer price revised. 205 are revised down and 512 are revised up. Low, Medium and High have 1,371, 2,734 and 3,100 deals, respectively. 4.9%, 2.6% and 2.1% are revised down, and 8.9 %, 5.7% and 7.5% are revised up for the three portfolios of deals. Conditional on downward revision, the average revision ratios (defined as final offer/initial offer-1) are -8.80%, -15.01% and -18.20% for Low, Medium, and High, respectively. Conditional on upward revision, the average revision ratios are 18.88%, 16.17%, and 19.24%, respectively. The targets in the Low portfolio have higher downward revision probabilities, but, conditional on downward revision, the revision ratio is lower. These targets also have higher upward revision probabilities. Overall, the revision analysis does not reveal evidence

[22] The results are robust if I analyse the effect of revisions using the whole sample. For details, see Part III of the Appendix.

that revisions favor my portfolios differentially. Still, I recalculate the portfolio returns by excluding the deals with offer price revisions. The results in Panel E of Table 7 show that the five-factor alpha is 1.800%. This is slightly lower than the alpha (2.115%) in the same time period without excluding offers with revisions. But the change is relatively small.

Second, to gauge the effect of uncertainty about the entry of competing offers, I build a new deal failure probability model which explicitly takes competing offers into account. Specifically, I redefine deal failure as targets that are not acquired by any acquirers in a specific period after deal announcement (365 days in the empirical analysis). Different from the previous definition of deal failure, the new definition excludes the deals in which the target is acquired by *some other acquirer*. I use the same set of independent variables as in Table 2 to model deal failure probability and calculate the Low-High portfolio returns. I report the five-factor analysis of the Low-High portfolio in Panel F of Table 7. The results show that the Low-High alpha is 1.319%; this is significant at the 1% level, suggesting that considering competing offers strengthens the results.

4.6 Testing alternative hypotheses

4.6.1 Skewness preference without probability weighting

As shown in Table 3, target stocks in deals with low failure probability are more negatively skewed than target stocks in other categories. Many traditional utility functions feature skewness preference, for example, CRRA utility.[23] When investors care about diversification and do not face frictions to do so, coskewness will affect asset prices but idiosyncratic skewness will not (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000).

[23] An investor's expected utility of end of period wealth, $E[U(W)]$, can be expressed, by Taylor expansion, as $U(W_0)+[U''(W_0)/2!]\sigma_w^2+[[U'''(W_0)/3!]s_W^3$+terms of higher orders, where W_0 is the mean of W, σ_w^2 is the variance of W, and s_W^3 is the skewness of W. Typically, $U''<0$, implying aversion for variance, and $U'''>0$, implying preference for skewness. For CRRA utility, $U(W)=(1-\theta)^{-1}W^{1-\theta}$ ($\theta>0$ and $\theta\neq1$), $U'''= \theta(\theta+1) W^{\theta+2}$, which is greater than 0, implying skewness preference (Kraus and Litzenberger, 1976).

As shown in Table 6, the Low-High portfolio has negative coskewness risk. Therefore, my findings cannot be explained by the traditional models without frictions to diversify. However, in the real world, investors are not well-diversified (Odean, 1999; Mitton and Vorkink, 2007; Goetzmann and Kumar, 2008).[24] Under-diversification leads to the pricing of idiosyncratic skewness. I thus examine whether skewness preference without probability weighting can explain my findings in a world in which investors cannot fully diversify. For simplicity, I assume that investors cannot diversify at all.

I model the expected stock return of a target stock as shown in Figure 1. I choose CRRA utility as perhaps it is the most widely used utility function in the finance literature. The CRRA utility is $U_{CRRA}=-C^{1-\eta}$, where C is the consumption, and η is the relative risk aversion coefficient. A narrow framing CRRA investors will value the target stock as:

$$U(P)=\pi U(P_{alone})+(1-\pi)U(P_{offer}). \tag{8}$$

The target stock expected return is defined as

$$ER= [\pi P_{alone}+ (1-\pi)P_{offer}]/P-1. \tag{9}$$

The target standalone value P_{alone} is standardized to 1, and P_{offer} is chosen to be 1.30. 30% is to match the average merger and acquisition premium from the data. From these assumptions, we can calculate the target stock expected return.

[Insert Figure 6 here]

Figure 6 shows the expected target stock returns with respect to deal failure probability, for five risk aversion coefficients ranging from 1 to 5. We can see from Figure 6, though CRRA utility functions have feature of positive skewness preference, the skewness effect is dominated by aversion to variance, thus target expected return is highest when deal failure probability is moderate. This contradicts my finding that targets in deals with

[24] There are many plausible explanations for lack of diversification, such as the fixed trading costs (Brennan, 1975), search costs (Merton, 1987), or returns to specialization in information acquisition (Van Nieuwerburgh and Veldkamp, 2010).

moderate failure probability have a lower return than targets in deals with low failure probability.

4.6.2 The disposition effect

Grinblatt and Han (2005), and Frazzini (2006) argue that the disposition effect can lead to excess selling after price increases, which drives the current stock price below fundamental value and consequently yields higher future stock returns. Typically, an M&A announcement is "good news" for the target shareholders; the disposition effect will therefore predict an under-reaction. This effect may be stronger for deals with low failure probability as their initial price run-up is likely to be higher. In other words, in deals with low failure probability, the target price will increase more on announcement, which will mean higher capital gains for existing shareholders. The disposition effect will make these shareholders more likely to sell the stock. This may depress the stock's price beyond fundamentals and thereby lead to higher returns in the near future.

I use the cross-sectional regression framework of Baker and Savasoglu (2002) to test this alternative explanation. As in Baker and Savasoglu (2002), the dependent variable is the realized target return from 3 days after deal announcement to 25 trading days after deal announcement. The key independent variable is deal failure probability π. Overweighting of small probabilities predicts that the coefficient on π is negative. I include the target past return and the target announcement return in the regression to capture the impact of the disposition effect. Since the returns are overlapping in time and thus are not independent, I cluster the standard errors by month following Rogers (1993).

$$R_{tgt,3\text{-}25} = a + \beta_1 \pi_i + \beta_2 TargetPastReturn_i + \beta_3 TargetAnnouncementReturn_i + Controls + \varepsilon_i \qquad (10)$$

[Insert Table 8 here]

Table 8 shows the results. Model (1) reports the univariate regression results. As expected, the coefficient of π is significantly negative, confirming the previous results based on the calendar-time portfolio method. In model (2), I control for other deal characteristics, such as the attitude of the target, payment method, and target size. In the stylized model shown in Figure 1, π*(1-π) measures the volatility of the target stock return. So, following Baker and Savasoglu (2002), I also control for π*(1-π). Target Size is the natural logarithm of target firm market capitalization 22 trading days prior to deal announcement. After controlling for these factors, the coefficient of π is still significantly negative.

In Models (3), (4) and (5), I test whether the disposition effect can explain my results by including target past return and the target announcement return as regressors. The coefficients on these regressors are both positive, consistent with the prediction of the disposition effect hypothesis. However, controlling for them decreases the magnitude of the coefficient of π by only around 20%, and therefore does not change my main conclusion, as the coefficient of π is still significantly negative.

4.7 Limits to arbitrage

It is reasonable to think that arbitrageurs may not overweight small deal failure probability. However, why they cannot arbitrage away the positive abnormal return of the Low-High portfolio? I therefore examine whether there are any limits to arbitrage that prevent arbitrageurs from doing so?

My study is related to a popular hedge fund trading strategy called merger arbitrage. After deal announcement, the target stock price is typically lower than the offer price. Merger arbitrage refers to the strategy that attempts to profit from this spread. In doing so, arbitrageurs buy the target stock, and if the offer involves stock, sell short the acquirer stock to hedge the risk of fluctuations in the acquirer stock price. Evidence shows that merger arbitrageurs have a significant impact on target prices during acquisition deals. If limits to arbitrage help to explain the undervaluation of targets in deals with low failure probability, we would expect that the relation between deal failure probability and target returns to be stronger when arbitrage is more difficult.

Starting with the model specification in equation (10), I add interaction terms between deal failure probability and proxies for limits to arbitrage to examine whether limits to arbitrage moderate the relation between deal failure probability and target returns.

$$R_{tgt,3\text{-}25} = a + \beta_1\pi_i + \beta_2 TargetPastReturn_i + \beta_3 TargetAnnouncementReturn_i + Controls$$
$$+\gamma\ Limit\text{-}to\text{-}Arbitrage_i + \eta\ Limit\text{-}to\text{-}Arbitrage_i{*}\pi_i + \varepsilon_i \qquad (11)$$

If limits to arbitrage constrain the ability of arbitrageurs to arbitrage away the mispricing, we would expect the inverse relationship between π and $R_{tgt,3\text{-}25}$ to be stronger when arbitrage is more difficult.

The limits to arbitrage literature emphasizes the role of limited capital. In the presence of slow moving capital, merger arbitrage capital is more likely to be constrained if merger arbitrageurs have experienced losses in the recent past (Baker and Savasoglu, 2002; Mitchell, Pedersen and Pulvino, 2007; Mitchell and Pulvino, 2012) or when more arbitrage capital is needed (Baker and Savasoglu, 2002). I use the total market capitalization of failed deals in the past 365 days to proxy for arbitrageurs' recent losses and use the total market capitalization of pending deals to proxy for the needed capital.

Model (1) of Table 9 shows that the interaction between deal failure probability and cumulated arbitrageur losses is negative. Model (2) shows that the interaction between deal failure probability and needed arbitrage capital is also negative. Both results are consistent with the conjecture that limited capital constrains arbitraging activities.

[Insert Table 9 here]

Another measure of limit to arbitrage is based on payment type. The difficulty of arbitrage depends on the payment method. In cash deals, arbitrageurs only need to have a position in the target stock; but in stock deals, they need to have two positions: a long position in the target stock and a short position in the acquirer stock. The arbitrageurs incur direct costs for both the long and the short positions, and often do not receive the full interest on the short sale proceeds (Baker and Savasoglu, 2002). Using proprietary equity loan data, Geczy, Musto, and Reed (2002) find that acquirers' stock is expensive to borrow and accounting for short selling costs decreases arbitrage profits significantly.[25] Such arbitrage difficulty is likely to be lower for cash deals than for stock deals.

The results are shown in model (3) in Table 9. The prediction here is that the relation between deal failure probability and target returns should be weaker for cash deals. In model (3), the interaction between deal failure probability and Pure Cash is positive, and the interaction between deal failure probability and Pure Stock is negative though not statistically significant, consistent with the argument that cash deals are easier to arbitrage than other deals.

Firm size is another variable widely used to measure arbitrage difficulty. However, in merger arbitrage, the relation between firm size and arbitrage difficulty is ambiguous. On one hand, larger firms are more liquid and may attract more arbitrageurs. On the other hand, Baker and Savasoglu (2002) argue that larger targets need more arbitrage capital; they find that larger target firms indeed have higher returns. In Table 8, target size is positive in all four models with target size as a control and is significant in three of them. Nevertheless, I report the result of using firm size as a measure of limits to arbitrage in model (4) of Table 9. However, I do not find that target firm size significantly moderates the relation between deal failure probability and target returns.

[25] Geczy, Musto, and Reed (2002) analyse equity loans for initial public offerings, DotCom stocks, large cap stocks, growth stocks, low-momentum stocks and acquirers' stocks in merger arbitrage. They conclude that "the effect of short-selling frictions appears strongest in merger arbitrage".

4.8 Probability estimation errors or overweighting objective probability?

Probability weighting can be driven either by erroneous beliefs about the objective probability (probability estimation errors) or by investors simply assigning a disproportionately higher weight on small deal failure probabilities (overweighting objective probability). The asset pricing implications are the same, but some subtle differences exist. If probability weighting is driven by probability estimation errors, the abnormal returns reflect mistakes made by investors. But if probability weighting is driven by overweighting objective probability, the abnormal returns reflect investors' inherent risk attitudes. These alternatives are difficult distinguish from one another. Though a thorough disentanglement is beyond the scope of this paper, in this section I present some discussion and indicative evidence that may shed some light on this issue.

Most of the literature on overweighting objective probability adopts constant probability weighting functions that are independent of the outcomes attached to the probability (Quiggin, 1982; Yaari, 1987; Prelec, 1998; Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Though several authors propose probability weighting functions that are dependent on the outcomes, it is hard to apply them to the financial markets.[26] On the other hand, we have more evidence on when investors are more likely to make errors. Therefore, I focus on testing implications of probability estimation errors.

Though errors could occur for many reasons, recent literature has focused on one reason: inattention. Scholars argue that attention is a scarce cognitive resource and that the

[26] For example, Rottenstreich and Hsee (2001) argue that kissing a movie star is likely to be more affect-rich than a cash equivalent of the kiss and find that decision makers exhibit more overweighting of small probabilities when the outcome is more affect-rich. In financial markets, everything is measured in dollars; it is therefore hard to predict when a deal failure will be more affect-rich.

allocation of attention can explain a variety of financial phenomena.[27] If inattention is the driver of errors, it may also cause errors in probability estimation.

Following the existing literature, I choose three measures to proxy for investor attention: the number of concurrent M&A deals, whether the deal is announced on Friday, and abnormal trading volume. Hirshleifer, Lim, and Teoh (2009) find that concurrent news will distract investor attention, and DellaVigna and Pollet (2009) find that investors are less attentive on Fridays than on other weekdays. I expect that a greater number of concurrent deals is likely to lead to investor inattention and that deals announced on a Friday will attract less attention.[28] Number of concurrent deals is calculated as the total number of deals announced on the same day. In order to mitigate the effect of extreme observations, I take the natural logarithm.[29] My final measure of investor attention is based on abnormal trading volume of the target stock in the deal announcement period. If a deal attracts more attention, its trading volume is likely to be higher (Barber and Odean, 2008; Gervais, Kaniel, and Mingelgrin, 2001). Abnormal volume is measured as the log ratio of target turnover from 22 trading days before deal announcement to 2 days after deal announcement and

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[27]Examples of such finance applications are: investor trading behavior (Barber and Odean, 2008; Seasholes and Wu, 2007; Yuan, 2012), stock return behavior after corporate disclosure such as post earnings announcement drift (Hirshleifer and Teoh, 2003; Hirshleifer, Lim, and Teoh, 2009; DellaVigna and Pollet, 2009), high volume premium (Gervais, Kaniel, and Mingelgrin, 2001), market making activities of NYSE specialists (Corwin and Coughenour, 2008), return comovement (Barberis and Shleifer, 2003; Peng and Xiong, 2006), return cross-autocorrelation (Cohen and Frazzini, 2008; Cohen and Luo, 2012; Cen, Chan, Dasgupta, and Gao, 2013), IPO underpricing and long term underperformance (Da, Engelberg, and Gao, 2011), and stock reaction to stale information (Huberman and Regev, 2001; Gilbert, Kogan, Lochstoer, and Ozyildirim, 2012), among others.

[28] Conceptually, the number of concurrent deals is likely to be correlated with the availability of arbitrage capital at the arbitrageurs' disposal to attack a particular mispricing. Given that I find evidence of limits to arbitrage, using number of concurrent deals to proxy for inattention might be likely to falsely attribute to inattention what truly is an effect of limits to arbitrage. However, this may not be a problem for two reasons. First, empirically, the number of concurrent deals and the total market capitalization of pending deals are only weakly correlated (correlation coefficient is 0.052). Second, I do not find significant results using the number of concurrent deals. As the number of concurrent deals is likely to be correlated with the availability of arbitrage capital, using it as a measure of inattention may bias the results of favouring finding evidence supporting limited attention. The fact that the number of concurrent deals does not have a significant moderating effect weakens the concern.

[29] The results are similar if I use the raw number.

the average turnover from 365 days to 22 trading days prior to deal announcement. On average, there are 4.96 deals pending (maximum is 17), 17.12% deals are announced on a Friday, and the trading volume in the announcement period is 2.22 times the average trading volume prior to announcement.

First, I evaluate whether these proxies are good measures of attention and how deal failure probability is related to my attention proxies. I link my attention proxies to a direct measure of attention based on Google Search Volume Index (SVI)[30]. SVI is aggregate search frequency in Google. Da, Engelberg, and Gao (2011) is the first paper to use this measure. I use the log difference in average SVI between the four weeks ending at the week of deal announcement and the 48 weeks ending 4 weeks before deal announcement as the measure of attention. I call this measure abnormal SVI. In the end, I have 871 cases with valid abnormal SVI. On average, SVI increases by 40% around the deal announcement. Its correlations with the number of concurrent deals, a Friday dummy, and abnormal turnover are -0.037, -0.046, and 0.270, respectively. Though all correlations are of the expected sign, the magnitudes of the first two are small.

Second, I examine whether on average, deals with low failure probability capture less investor attention. A priori, this is unlikely to be true, since the target stocks with low failure probability have higher announcement returns, and previous studies document that larger returns are more salient and are likely to attract more attention (Seasholes and Wu, 2007; Barber and Odean, 2008), and that investors are less likely to underreact for such assets (Choi and Hui, 2013; Klibanoff, Lamont, and Wizman, 1998). As expected, π is significantly correlated with abnormal trading volume (correlation coefficient is -0.097, significant at 1% level) and abnormal SVI, but is positively correlated with the Friday

[30] Following Da et al. (2011), I use the stock ticker to search and exclude the weeks that SVI is missing or zero. SVI is available from 2004 to 2010. As SVI is only available for 871 cases in the sample, I do not use it in the multivariate regressions.

dummy (correlation coefficient is 0.023, significant at 1% level) and the number of concurrent deals (correlation coefficient is 0.126, significant at 1% level). Overall, the results are mixed.

[Insert Table 10 here]

Third, I examine whether inattention strengthens the relation between deal failure probability and target stock returns. If inattention is the driving force that leads to errors in probability estimation, we should expect so. Table 10 reports the results. As in Table 9 when testing limit to arbitrage, I add terms that interact π and the attention proxies to test the inattention hypothesis. The interaction term is significant in none of the three models. Overall, I do not find evidence supporting that inattention is the driving force for the findings, thus fail to support the probability estimation error view.

5. Conclusion

A large body of experimental evidence shows that decision makers tend to overweight the probability of tail events. This paper provides direct evidence on probability weighting using data from mergers and acquisitions. I estimate the deal failure probability based on (1) deal characteristics, and (2) by comparing the target price and the offer price. Next, I test for probability overweighting by examining the future target stock returns, conditional on the ex-ante failure probability of the deal. Overweighting small failure probabilities lowers the target stock price and yields positive abnormal future stock returns. I confirm this prediction and find that the target stocks with low failure probability yield significant positive stock returns in the period between deal announcement and deal resolution, even though these deals have lower beta and downside risk than the other deals.

There are at least two paths for further research. First, probability weighting can be driven by either erroneous beliefs about the objective probability or by investors simply overweighting tail event in their preferences. I try to distinguish between these two possibilities in Section 4.8 and show preliminary evidence that appears inconsistent with the former. However, this evidence is not conclusive. Further research in this direction is needed. Second, Cornelli and Li (2002) and Hsieh and Walkling (2005) show that merger arbitrageurs play an important role in solving the free rider problem inherent in mergers and acquisitions. It may be interesting to examine further how investors' overweighting of small deal failure probabilities affects trading behavior of the merger arbitrageurs, and how this might affect the incentives of potential bidders to launch a takeover bid.

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Table 1. Sample.

This table details the sample used in this paper. Duration is the number of calendar days between deal announcement and deal completion or withdrawl. Hostile is a dummy variable which is equal to 1 if the initial reception of the target is hostile or unsolicited, 0 otherwise. Pure Cash (Pure Stock) is a dummy variable which is equal to 1 if the consideration of the deal is all in cash (stock), 0 otherwise. Tender, LBO and MOE dummy variables indicate tender offer, leveraged buyout and merger of equals, respectively. Pct Held is the percentage of shares held by the acquiring firm six months prior to deal announcement. Toehold is a dummy variable which is equal to 1 if Pct Held is no less than 5%, 0 otherwise. Cleanup is a dummy variable which is equal to 1 if Pct Held is no lower than 50%, 0 otherwise. Public Acquirer is a dummy variable indicating the public status of the acquirer. Target Past return is the cumulative return from 365 calendar days before deal announcement ending 22 trading days prior to deal announcement. Target Size is the natural logarithm of target firm market capitalization (measured at the constant 2005 dollar) 22 trading days prior to deal announcement. Prior Bid is a dummy variable which is equal to 1 if the target company received another takeover bid in the past 365 days, and 0 otherwise. Cross Border, Same State and Same Industry are three dummy variables indicating whether the acquirer is a foreign company, whether the acquirer and the target are from the same state, and whether the acquirer and the target are from the same 2-digit SIC industry, respectively. Completed (withdrawn) is a dummy variable which is equal to 1 if the deal is completed (withdrawn), 0 otherwise. The sample runs from January 1981 to December 2010.

Year	N	Duration Mean	Duration Median	Hostile	Pure Cash	Pure Stock	Tender	LBO	MOE	Pct Held	Toehold	Cleanup	Public Acquirer	Target Past Return	Target Size	Prior Bid	Cross Border	Same State	Same Industry	Completed	With-drawn
<=1983	743	164	97	5	141	88	244	40	0	4.92	120	24	474	28.53	11.69	166	91	277	358	464	227
1984	515	144	105	7	148	37	158	63	0	4.78	88	15	270	4.05	11.77	141	82	174	199	285	166
1985	470	128	98	24	237	55	146	52	1	3.85	67	10	295	14.14	12.07	170	43	142	187	247	123
1986	587	142	98	34	317	54	185	48	0	3.44	97	5	299	20.66	11.94	197	83	156	231	330	153
1987	674	138	93	108	323	49	175	74	0	5.57	156	20	324	11.51	11.99	269	122	173	254	349	203
1988	944	164	110	138	475	51	251	136	0	5.15	186	29	379	-7.40	11.75	389	196	198	275	436	310
1989	996	163	115	69	438	79	193	78	0	4.53	177	35	346	18.79	11.74	391	226	213	303	445	240
1990	667	149	93	29	280	63	108	21	0	5.44	133	28	259	-11.21	11.51	217	166	155	219	354	110
1991	613	143	93	18	177	75	79	12	1	5.04	113	23	265	-2.69	10.94	192	120	145	211	344	112
1992	550	144	107	24	189	86	70	14	7	5.17	99	20	268	21.92	10.90	160	96	135	221	324	77
1993	584	131	104	24	237	90	79	10	2	4.88	101	21	301	30.11	11.38	155	106	165	248	368	99
1994	757	134	98	34	311	157	112	13	4	4.33	105	25	425	4.41	11.39	199	131	176	330	482	133
1995	785	128	99	54	313	178	117	16	7	3.60	95	21	455	6.87	11.44	188	132	182	336	503	115
1996	816	115	91	45	331	173	134	16	11	3.61	108	19	472	15.75	11.72	197	94	214	379	566	102
1997	832	134	107	46	290	235	177	25	12	3.74	78	27	569	14.52	11.86	176	97	250	420	623	124
1998	817	128	111	43	318	254	151	34	11	3.77	72	29	569	6.60	12.05	131	108	219	435	608	115
1999	871	127	102	64	366	224	195	47	11	3.31	84	23	606	10.16	12.11	135	105	230	446	671	127
2000	870	114	91	60	402	183	220	64	12	5.02	108	47	579	20.75	12.20	173	146	211	401	608	134
2001	527	118	100	29	226	114	119	26	13	5.57	77	26	365	-17.21	11.46	80	65	156	276	406	70
2002	337	120	94	35	183	49	86	29	3	8.11	59	29	204	1.83	11.17	35	36	112	170	251	51
2003	382	131	106	35	200	45	84	23	5	5.48	49	21	233	11.52	11.39	43	30	138	218	285	49
2004	304	141	127	29	142	36	45	30	7	3.71	27	13	209	39.17	12.18	33	27	101	173	238	34
2005	356	129	109	41	216	38	70	38	4	4.80	43	17	219	6.38	12.58	44	41	93	179	268	49
2006	408	132	106	28	266	26	64	67	4	2.16	31	5	235	8.64	12.89	51	48	107	208	303	49
2007	444	126	107	25	287	31	99	64	4	3.04	38	15	258	7.98	13.10	66	66	133	220	332	62
2008	425	103	77	52	253	26	86	23	1	2.90	50	8	197	-32.32	12.43	60	63	93	194	237	75
2009	325	102	81	24	143	36	74	21	2	5.16	38	18	151	-13.94	11.61	67	45	98	142	211	36
2010	307	86	81	20	184	19	57	39	5	2.48	20	7	150	53.01	12.22	42	39	72	157	154	22
Total	16906	134	100	1144	7393	2551	3578	1123	127	4.41	2419	580	9376	9.65	11.80	4167	2604	4518	7390	10692	3167

Table 2. Modelling deal failure probability

This table presents the models used to calculate deal failure probability. The dependent variable is a dummy variable which is equal to 1 when the deal is completed, 0 if the deal is withdrawn. Hostile is a dummy variable which is equal to 1 if the initial reception of the target is hostile or unsolicited, 0 otherwise. Pure Cash (Pure Stock) is a dummy variable which is equal to 1 if the consideration of the deal is all in cash (stock), 0 otherwise. Tender, LBO and MOE dummy variables indicate tender offer, leveraged buyout and merger of equal, respectively. Pct Held is the percentage of shares held by the acquiring firm six months prior to deal announcement. Toehold is a dummy variable which is equal to 1 if Pct Held is no less than 5%, 0 otherwise. Cleanup is a dummy variable which is equal to 1 if Pct Held is no lower than 50%, 0 otherwise. Public Acquirer is a dummy variable indicating the public status of the acquirer. Target Past return is the cumulative return from 365 calendar days before deal announcement ending 22 trading days prior to deal announcement. Target Size is the natural logarithm of target firm market capitalization 22 trading days prior to deal announcement. Prior Bid is a dummy variable which is equal to 1 if the target company received another takeover bid in the past 365 days, and 0 otherwise. Cross Border, Same State and Same Industry are three dummy variables indicating whether the acquirer is a foreign company, whether the acquirer and the target are from the same state, and whether the acquirer and the target are from the same 2-digit SIC industry, respectively. $(P_{offer} - P)/(P_{offer} - P_{alone})$ is the price-based failure probability, where P_{offer}, P and P_{alone} are the offer price, the post-announcement target stock price and the target standalone value which is proxied by the target price 22 trading days prior to deal announcement. I use logistic regression to estimate these models. The standard errors are clustered by month. The White-heterogeneity consistent t-statistics are reported in the parentheses. The sample runs from 1981 to 2010 and include all the deals with known deal status.

	(1)	(2)	(3)	(4)	(5)	(6)		(7)	
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Margin	Coeff.	Margin
Hostile	1.914***					2.597***	0.565***		
	(13.47)					(15.92)	(18.29)		
Pure Cash		-0.514***				-0.556***	-0.082***		
		(-7.60)				(-8.21)	(-7.88)		
Pure Stock		-0.669***				-0.371***	-0.051***		
		(-8.94)				(-4.93)	(-5.23)		
Tender		-0.882***				-0.935***	-0.118***		
		(-11.36)				(-10.47)	(-12.88)		
LBO		0.862***				0.807***	0.146***		
		(10.67)				(9.00)	(7.77)		
MOE		0.119				0.410*	0.069		
		(0.51)				(1.78)	(1.60)		
Pct Held		-0.028***				-0.021***	-0.003***		
		(-5.93)				(-4.50)	(-4.43)		
Toehold		1.023***				0.625***	0.106***		
		(9.07)				(5.52)	(4.84)		
Cleanup		0.542**				0.516**	0.088*		
		(2.21)				(2.04)	(1.80)		
Public Acquirer			-0.688***			-0.298***	-0.045***		
			(-14.83)			(-5.02)	(-4.88)		
Target Past Return				-0.177***		-0.158***	-0.023***		
				(-4.56)		(-3.95)	(-4.00)		
Target Size				-0.064***		-0.079***	-0.012***		
				(-4.61)		(-5.14)	(-5.13)		
Prior Bid					0.849***	0.834***	0.142***		
					(17.83)	(16.26)	(14.04)		
Cross Border					0.092	0.195**	0.030**		
					(1.22)	(2.47)	(2.36)		
Same State					-0.262***	-0.089	-0.013		
					(-4.70)	(-1.50)	(-1.52)		
Same Industry					-0.421***	-0.123**	-0.018**		
					(-8.42)	(-2.11)	(-2.11)		
$(P_{offer} - P)/(P_{offer} - P_{alone})$								2.195***	0.319***
								(15.70)	(14.23)
Constant	-1.370***	-0.956***	-0.940***	-0.607***	-1.318***	-0.118		-2.297***	
	(-35.54)	(-16.07)	(-20.67)	(-3.66)	(-31.85)	(-0.65)		(-27.11)	
Pseudo R^2	0.014	0.050	0.019	0.006	0.037	0.101		0.059	
Obs.	13582	13582	13582	13582	13582	13582		4325	

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 3. Target stock characteristics

This table presents the return characteristics of individual target stocks. Panel A reports the target stock characteristics except for their return moments, and Panel B reports the return moments. Low, Medium, and High indicate the deals with failure probability lower than 10%, between 10% and 20%, and others, respectively. Deal failure probability is modelled based on model (6) of Table 2. Duration is the number of calendar days between deal announcement and deal completion or withdrawal. Premium is the natural log difference between the initial offer price and the target stock price 22 trading days before deal announcement. I use two methods to calculate the characteristics of individual stocks: one based on the realized returns (physical moments) and one based on the options prices (risk neutral moments). Realized returns are the buy and hold return from the end of the second day after deal announcement to 180 days after deal announcement or deal resolution, whichever comes first. I calculate the physical moments from the cross-section of target stocks within each of the three groups. To mitigate the effect of extreme returns, I calculate the physical moments from log returns rather than raw returns. For risk neutral moments, I calculate stock by stock as long as there is a large enough number of options available. The detailed methodology can be found in Part II of the Appendix. The statistical significance between median duration of Low and High is tested using the Brown and Mood (1951) median tests. I use bootstrap test (with 1000 round resampling) to tests whether the differences between the physical moment is significant. All the other tests are the standard two sample t-tests. The sample period is from January 1984 to December 2010.

Panel A. Target stock characteristics except their return moments

	Failure probability	Mean Deal duration	Median Duration	Premium
Low	0.052	100.87	62	0.353
Medium	0.154	137.44	113	0.354
High	0.362	142.94	107	0.382
Low-High	0.310***	42.07***	45***	0.029

Panel B. Target stock return moments

	Physical Moments			Risk Neutral Moments		
	N	Standard Deviation	Skew	N	Standard Deviation	Skew
Low	3233	0.216	-3.249	199	0.153	-1.503
Medium	4380	0.270	-2.817	486	0.172	-1.245
High	8550	0.389	-2.043	472	0.196	-1.275
Low-High		0.173***	-1.206**		0.043***	0.228**

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 4. Portfolio characteristics

This table presents the return characteristics of the portfolios. Low, Medium, and High indicate the deals with failure probability lower than 10%, between 10% and 20%, and others, respectively. The deal failure probability is modelled based on model (6) of Table 2. I begin to include a target stock into one of the three portfolios from the end of the second day after the deal announcement. The holding period ends when time since announcement exceeds 180 days or when the deal is completed or withdrawn, whichever comes first. Value weighted daily returns are compounded into monthly returns. Reported are the characteristics of the three portfolios and a zero-investment portfolio which buys long the Low portfolio and sells short the High portfolio. The sample period is from January 1984 to December 2010.

	Mean	t-stat	Standard Deviation	Sharpe Ratio	Skewness
Low	1.170***	4.37	0.167	1.106	0.558
Medium	0.494	1.58	0.195	0.529	-1.252
High	0.377	1.04	0.226	0.393	-1.436
Low-High	0.793**	2.37	0.209	0.456	0.915

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5. Five factor-adjusted portfolio performance

This table presents the risk-adjusted portfolio performance of Low, Medium, High and Low-High. Low, Medium, and High indicate the deals with failure probability lower than 10%, between 10% and 20%, and others, respectively. Deal failure probability is modelled based on model (6) of Table 2. I begin to include a target stock into one of the three portfolios from the end of the second day after the deal announcement. The holding period ends when time since announcement exceeds 180 days or when the deal is completed or withdrawn, whichever comes first. Value weighted daily returns are compounded into monthly returns. Reported are the alphas of the three portfolios and a zero-investment portfolio which buys long the Low portfolio and sells short the High portfolio. MktRf, SMB, HML, UMD and PS Liquidity represent the market factor, Small-minus-Big factor, High-minus-Low factor, the momentum factor and the Pastor and Stambaugh (2003) liquidity factor, respectively. The sample period is from January 1984 to December 2010.

	Alpha (%)	MktRf	SMB	HML	UMD	PS Liquidity	R^2	N
Low	0.808***	0.633***						
	(3.77)	(13.70)					0.368	324
	0.766***	0.588***	0.337***	0.046	-0.025	0.065		
	(3.55)	(12.02)	(4.93)	(0.63)	(-0.55)	(1.18)	0.416	324
Medium	0.008	0.851***						
	(0.03)	(17.51)					0.488	324
	-0.038	0.865***	0.242***	0.228***	0.038	-0.137**		
	(-0.17)	(16.75)	(3.35)	(2.95)	(0.81)	(-2.38)	0.523	324
High	-0.198	1.007***						
	(-0.77)	(18.26)					0.509	324
	-0.293	1.057***	0.261***	0.520***	-0.070	-0.137**		
	(-1.18)	(18.87)	(3.33)	(6.20)	(-1.37)	(-2.19)	0.581	324
	1.006***	-0.374***						
	(3.11)	(-5.36)					0.082	324
	1.060***	-0.470***	0.076	-0.473***	0.045	0.202**		
Low-High	(3.29)	(-6.43)	(0.74)	(-4.33)	(0.68)	(2.47)	0.169	324

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 6. Downside risk and coskewness risk analysis

Panel A and Panel B report the results of analysing the downside risk and the coskewness risk of the Low-High portfolio, respectively. Low, Medium, and High indicate the deals with failure probability lower than 10%, between 10% and 20%, and others, respectively. Deal failure probability is modelled based on model (6) of Table 2. I begin to include a target stock into one of the three portfolios from the end of the second day after the deal announcement. The holding period ends when time since announcement exceeds 180 days or when the deal is completed or withdrawn, whichever comes first. Value weighted daily returns are compounded into monthly returns. The Low-High portfolio is the difference between the Low and the High portfolio.

In Panel A, the piecewise linear regression model is estimated

$$R_{portfolio,t}-R_f=(1-UP_t)[a_{low}+\beta_{low}(R_{m,t}-R_f)]+UP_t[a_{high}+\beta_{high}(R_{m,t}-R_f)]+\beta' X_t+\varepsilon_t$$

subject to: $a_{low}+\beta_{low}(Threshold)= a_{high}+\beta_{high}(Threshold)$

where $R_{portfolio,t}$ is the monthly return of the Low-High portfolio, $R_{m,t}$ is the value weighted market return, R_f is the risk free interest rate, and UP_t is a dummy variable which is equal to 1 when the market return is greater than a threshold. a_{low}, a_{high}, β_{low} and β_{high} are alphas and betas when market excess return is below or above a threshold, respectively. X represents the other factors. Three different threshold (-3%, -4%, and -5%) levels are analysed and reported. The coskewness mimicking factor is constructed following Harvey and Siddique (2000). Specifically, the 30% of stocks with the most negative coskewness in each month is classified into an S^- portfolio and the 30% of stocks with the most positive coskewness in each month is classified into an S^+ portfolio. As in Harvey and Siddique (2000), both S^-- S^+ and S^-- R_f are used as the coskewness hedged portfolio for the portfolio abnormal return calculation. The coskewness is calculated as

$$\widehat{\beta}_i=\frac{E[\varepsilon_{i,t}R^2_{m,t}]}{\sqrt{E[\varepsilon^2_{i,t}]E[R^2_{m,t}]}},$$

where $\varepsilon_{i,t}=R_{i,t}$ - a_i - $\beta_i R_{m,t}$, and $R_{i,t}$ and $R_{m,t}$ are the excess return for stock i and the excess return for the market. Coskewness is estimated based on the monthly data of the past five years. The sample period is from January 1984 to December 2010.

	Alpha high	Alpha low	beta high	beta low	SMB	HML	UMD	PS Liquidity	R^2	N
Panel A. Downside risk										
Threshold=-5%	0.560	-3.969***	-0.167*	-1.073***						
	(1.64)	(-2.82)	(-1.88)	(-5.24)					0.118	324
	0.556	-3.994***	-0.252***	-1.162***	0.119	-0.417***	0.068	0.226***		
	(1.62)	(-2.88)	(-2.73)	(-5.85)	(1.18)	(-3.86)	(1.03)	(2.82)	0.204	324
Threshold=-4%	0.479	-2.846**	-0.145	-0.976***						
	(1.36)	(-2.52)	(-1.54)	(-5.34)					0.117	324
	0.479	-2.850**	-0.231**	-1.063***	0.118	-0.419***	0.067	0.225***		
	(1.35)	(-2.56)	(-2.38)	(-6.00)	(1.17)	(-3.87)	(1.02)	(2.80)	0.203	324
Threshold=-3%	0.446	-1.606*	-0.148	-0.832***						
	(1.21)	(-1.77)	(-1.47)	(-5.08)					0.108	324
	0.457	-1.574*	-0.237**	-0.914***	0.113	-0.424***	0.067	0.220***		
	(1.23)	(-1.75)	(-2.29)	(-5.75)	(1.11)	(-3.90)	(1.02)	(2.72)	0.194	324
Panel B. Coskewness risk										
	Alpha	MktRf	SMB	HML	UMD	PS Liquidity	S^--S^+	S^-- R_f	R^2	N
	1.239***	-0.068	0.090	-0.404***	0.042	0.211**	-0.411*			
	(3.66)	(-0.28)	(0.88)	(-3.47)	(0.64)	(2.59)	(-1.71)		0.177	324
	1.077***	-0.481***	0.098	-0.382***	0.042	0.221***		-0.294**		
	(3.36)	(-6.60)	(0.96)	(-3.23)	(0.64)	(2.71)		(-2.00)	0.179	324

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 7. Robustness

This table presents the risk-adjusted portfolio performance of the Low-High portfolio. Low, Medium, and High indicate the deals with failure probability lower than 10%, between 10% and 20%, and others, respectively. Deal failure probability is based on model (6) in Table 2. I begin to include a target stock into one of the three portfolios from the end of the second day after the deal announcement. Except for Panel C, the holding period ends when time since announcement exceeds 180 days or when the deal is completed or withdrawn, whichever comes first. Value weighted daily returns are compounded into monthly returns. MktRf, SMB, HML, UMD and PS Liquidity represent the market factor, Small-minus-Big factor, High-minus-Low factor, the momentum factor and the Pastor and Stambaugh (2003) liquidity factor, respectively. Pure cash offers are the deals in which the consideration is all in cash. Deals involving change of corporate control are the deals in which acquirer owns less than 50% of target but seeks to own more than 50%. First offers are the deals in which the target company did not receive any offer in the past 365 days. Panel D reports the Low-High alpha using the target price-based failure probability measure in model (7) in Table 2. The sample period is from January 1984 to December 2010 except for Panel D and Panel E. The sample runs from January 1997 to December 2010 for Panel D and Panel E.

	Alpha (%)	MktRf	SMB	HML	UMD	PS Liquidity	R^2	N
Panel A. Sub-sample								
Pure cash offers	0.748*	-0.381***	-0.029	-0.270**	0.035	0.261***		
	(1.95)	(-4.39)	(-0.23)	(-2.07)	(0.45)	(2.69)	0.091	324
Deals involving change of	1.058**	-0.562***	0.091	-0.479***	0.249**	-0.019		
corporate control	(2.50)	(-5.87)	(0.68)	(-3.34)	(2.86)	(-0.18)	0.159	324
First offers	0.930***	-0.361***	0.209**	-0.167	0.073	0.138		
	(2.78)	(-4.76)	(1.97)	(-1.47)	(1.05)	(1.63)	0.096	324
Panel B. Sub-period								
	0.763*	-0.150	-0.517***	-0.112	-0.124	-0.069		
1984-1996	(1.94)	(-1.48)	(-3.15)	(-0.64)	(-0.92)	(-0.58)	0.077	156
	2.115**	-0.479**	-0.213	-0.459*	0.474***	0.405**		
1997-2010	(2.39)	(-2.50)	(-0.88)	(-1.86)	(3.21)	(2.02)	0.194	168
Panel C. Changing the holding period								
30 days	2.226***	-0.373***	-0.367**	-0.483***	-0.067	0.204		
	(4.51)	(-3.34)	(-2.35)	(-2.89)	(-0.66)	(1.64)	0.071	324
60 days	1.793***	-0.507***	-0.402***	-0.765***	-0.138	0.271**		
	(3.91)	(-4.88)	(-2.76)	(-4.92)	(-1.45)	(2.34)	0.138	324
100 days	1.064***	-0.488***	-0.233**	-0.503***	0.056	0.275***		
	(2.86)	(-5.80)	(-1.98)	(-3.99)	(0.73)	(2.93)	0.164	324
365 days	0.960***	-0.423***	0.038	-0.487***	0.027	0.237***		
	(3.14)	(-6.11)	(0.40)	(-4.70)	(0.44)	(3.07)	0.171	324
Panel D. Price-based measure								
	1.040*	-0.598***	0.253*	-0.921***	0.123	0.188		
	(1.92)	(-5.03)	(1.70)	(-5.82)	(1.31)	(1.51)	0.307	168
Panel E. Excluding deals with offer price revisions								
	1.800***	-0.708***	-0.089	-0.592***	-0.040	0.356***		
	(3.10)	(-5.69)	(-0.57)	(-3.58)	(-0.41)	(2.66)	0.235	168
Panel F. Redefining deal failure								
	1.319***	-0.212**	-0.123	-0.268**	0.178**	-0.038		
	(3.41)	(-2.43)	(-1.00)	(-2.05)	(2.24)	(-0.39)	0.055	324

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 8. Testing the disposition effect

This table presents the results of testing the disposition effect, using cross-sectional regressions. The dependent variable is the cumulative return from the third trading day after deal announcement to 25 trading days after deal announcement or deal resolution, whichever is earlier. π denotes deal failure probability. It is calculated based on model (6) in Table 2. Hostile is a dummy variable which is equal to 1 if the initial reception of the target is hostile or unsolicited, 0 otherwise. Pure Cash (Pure Stock) is a dummy variable which is equal to 1 if the consideration of the deal is all in cash (stock), 0 otherwise. Target Size is the natural logarithm of target firm market capitalization 22 trading days prior to deal announcement. Target Past return is the cumulative from 365 days before deal announcement to 22 trading days prior to deal announcement. Target Announcement Return is the cumulative return from 22 trading days prior to deal announcement to 2 trading days after deal announcement. The standard errors are clustered by month. The White-heterogeneity consistent t-statistics are reported in the parentheses. The sample period is from January 1984 to December 2010.

	(1)	(2)	(3)	(4)	(5)
π	-0.081***	-0.068**	-0.063**	-0.063**	-0.057**
	(-6.45)	(-2.56)	(-2.37)	(-2.39)	(-2.18)
π (1-π)		-0.008	-0.010	-0.011	-0.014
		(-0.16)	(-0.20)	(-0.23)	(-0.28)
Hostile		0.051***	0.050***	0.046***	0.045***
		(4.34)	(4.25)	(3.92)	(3.82)
Pure Cash		0.002	0.002	0.001	0.001
		(0.48)	(0.47)	(0.25)	(0.23)
Pure Stock		0.022***	0.023***	0.021***	0.021***
		(6.11)	(6.33)	(5.64)	(5.84)
Target Size		0.002*	0.001	0.003**	0.002*
		(1.83)	(1.28)	(2.41)	(1.92)
Target Past Return			0.010**		0.010**
			(2.53)		(2.55)
Target Announcement Return				0.023***	0.024***
				(2.90)	(2.94)
Constant	0.005*	-0.032**	-0.025*	-0.044***	-0.038***
	(1.68)	(-2.24)	(-1.86)	(-3.08)	(-2.78)
adj-R^2	0.006	0.012	0.014	0.014	0.016
N	16163	16163	16163	16163	16163

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 9. Limits to arbitrage

This table presents the results of testing limits to arbitrage, using cross-sectional regressions. The dependent variable is the cumulative return from the third trading day after deal announcement to 25 trading days after deal announcement or deal resolution, whichever is earlier. π denotes deal failure probability. It is calculated based on model (6) in Table 2. Hostile is a dummy variable which is equal to 1 if the initial reception of the target is hostile or unsolicited, 0 otherwise. Pure Cash (Pure Stock) is a dummy variable which is equal to 1 if the consideration of the deal is all in cash (stock), 0 otherwise. Target Size is the natural logarithm of target firm market capitalization 22 trading days prior to deal announcement. Target Past return is the cumulative from 365 days before deal announcement to 22 trading days prior to deal announcement. Target Announcement Return is the cumulative return from 22 trading days prior to deal announcement to 2 trading days after deal announcement. Arbitrage capital loss is the total market capitalization of the failed deals in the past 365 days. Total market cap of pending deals is the total market capitalization of all the target companies that are pending at the announcement date of the target in question. The standard errors are clustered by month. The White-heterogeneity consistent t-statistics are reported in the parentheses. The sample period is from January 1984 to December 2010.

	(1)	(2)	(3)	(4)
π	-0.145***	-0.140***	-0.063**	-0.062
	(-4.02)	(-3.45)	(-2.18)	(-1.33)
π (1-π)	-0.010	0.001	-0.019	-0.014
	(-0.19)	(0.01)	(-0.39)	(-0.28)
Hostile	0.048***	0.047***	0.039***	0.045***
	(4.01)	(4.00)	(3.31)	(3.93)
Pure Cash	0.002	0.001	0.002	0.001
	(0.32)	(0.25)	(0.37)	(0.23)
Pure Stock	0.022***	0.020***	0.019***	0.021***
	(5.65)	(5.31)	(3.00)	(5.88)
Target Size	0.003***	0.002**	0.002*	0.002
	(2.72)	(2.46)	(1.86)	(1.01)
Target Past Return	0.010**	0.010**	0.010**	0.010**
	(2.35)	(2.38)	(2.54)	(2.54)
Target Announcement Return	0.024***	0.024***	0.023***	0.024***
	(3.03)	(3.01)	(2.87)	(2.95)
Arbitrage capital loss	0.000			
	(0.00)			
Arbitrage capital loss * π	-0.032***			
	(-2.60)			
Total market cap of pending deals		0.002		
		(0.41)		
Total market cap of pending deals * π		-0.048**		
		(-2.55)		
Pure Cash * π			0.007***	
			(2.88)	
Pure Stock * π			-0.045	
			(-1.59)	
Target Size*π				0.001
				(0.15)
Constant	-0.046***	-0.039**	-0.036***	-0.035
	(-3.25)	(-2.50)	(-2.65)	(-1.62)
adj-R^2	0.019	0.018	0.017	0.016
N	16163	16163	16163	16163

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 10. Probability estimation errors or overweighting objective probability?

This table presents the results of testing whether probability weighting is caused by probability estimation errors or by overweighting objective probability, using cross-sectional regressions. The dependent variable is the cumulative return from the third trading day after deal announcement to 25 trading days after deal announcement or deal resolution, whichever is earlier. π denotes deal failure probability. It is calculated based on model (6) in Table 2. Hostile is a dummy variable which is equal to 1 if the initial reception of the target is hostile or unsolicited, 0 otherwise. Pure Cash (Pure Stock) is a dummy variable which is equal to 1 if the consideration of the deal is all in cash (stock), 0 otherwise. Target Size is the natural logarithm of target firm market capitalization 22 trading days prior to deal announcement. Target Past return is the cumulative from 365 days before deal announcement to 22 trading days prior to deal announcement. Target Announcement Return is the cumulative return from 22 trading days prior to deal announcement to 2 trading days after deal announcement. Number of concurrent deals is the natural log of the number of deals announced on the same day as the focal target stock. Friday is a dummy variable if the deal is announced on Friday. Abnormal Volume is measured as the log ratio of target turnover during 5-day announcement window and the average turnover from 365 days before deal announcement to 22 trading days prior to deal announcement. The standard errors are clustered by month. The White-heterogeneity consistent t-statistics are reported in the parentheses. The sample period is from January 1984 to December 2010.

	(1)	(2)	(3)
π	-0.053	-0.063**	-0.063**
	(-1.40)	(-2.39)	(-2.38)
π (1-π)	-0.013	-0.012	-0.017
	(-0.27)	(-0.25)	(-0.35)
Hostile	0.045***	0.046***	0.040***
	(3.84)	(3.84)	(3.29)
Pure Cash	0.021***	0.021***	0.021***
	(5.83)	(5.82)	(5.82)
Pure Stock	0.002	0.001	0.001
	(0.31)	(0.24)	(0.18)
Target Size	0.002*	0.002*	0.002
	(1.81)	(1.94)	(1.64)
Target Past Return	0.010**	0.010**	0.010**
	(2.59)	(2.55)	(2.43)
Target Announcement Return	0.024***	0.024***	0.019**
	(2.95)	(2.94)	(2.10)
Number of concurrent deals	-0.005		
	(-1.13)		
Number of concurrent deals *π	-0.001		
	(-0.07)		
Friday		-0.004	
		(-0.67)	
Friday*π		0.027	
		(1.06)	
Abnormal turnover			0.001
			(0.26)
Abnormal turnover*π			0.022
			(1.49)
Constant	-0.031*	-0.037***	-0.034**
	(-1.96)	(-2.71)	(-2.47)
adj-R^2	0.017	0.016	0.017
N	16163	16163	16163

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

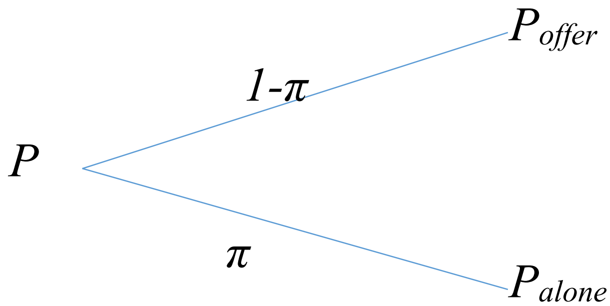

Figure 1. The payoff structure

P_{offer}, P_{alone}, and P represent the offer price, the target standalone price at the time of deal resolution and the post-announcement target stock price, respectively. π is deal failure probability.

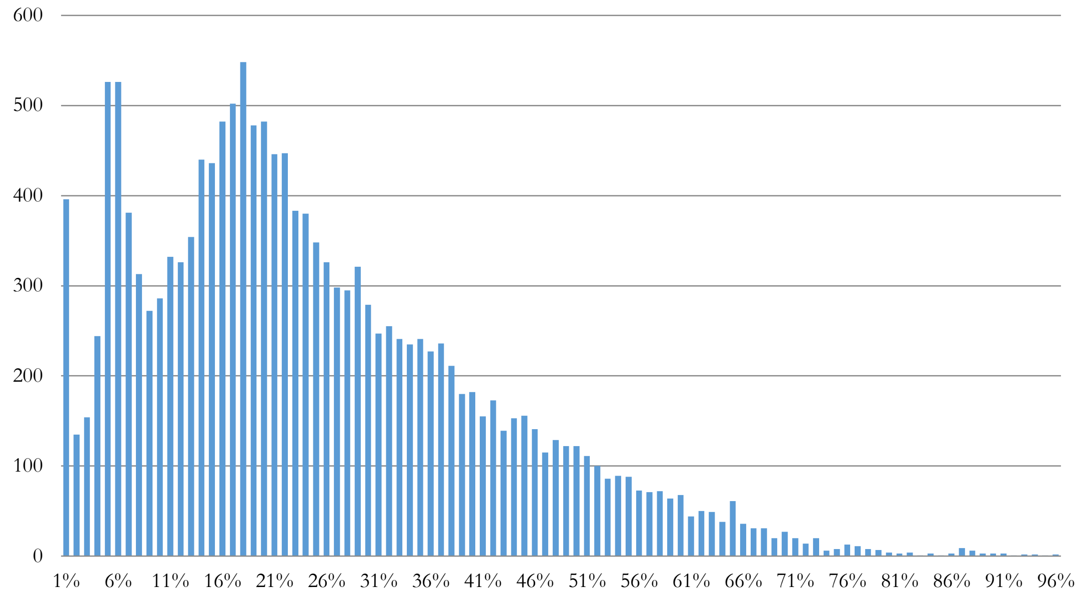

Figure 2. Distribution of deal failure probability

Deal failure probability is modelled based on a logistic model in which some deal characteristics and firm characteristics are used as the predictor. The detailed estimation model can be found in model (6) of Table 2. For the deals announced in year t, I use all the deals before year t to estimate the model coefficients. This figure shows the distribution of the deal failure probability of all the sample deals from 1984 to 2010. The x-axis is the deal failure probability and the y-axis is the number of deals with failure probability between (n-1) % and n%. There are no deals with failure probability above 96%.

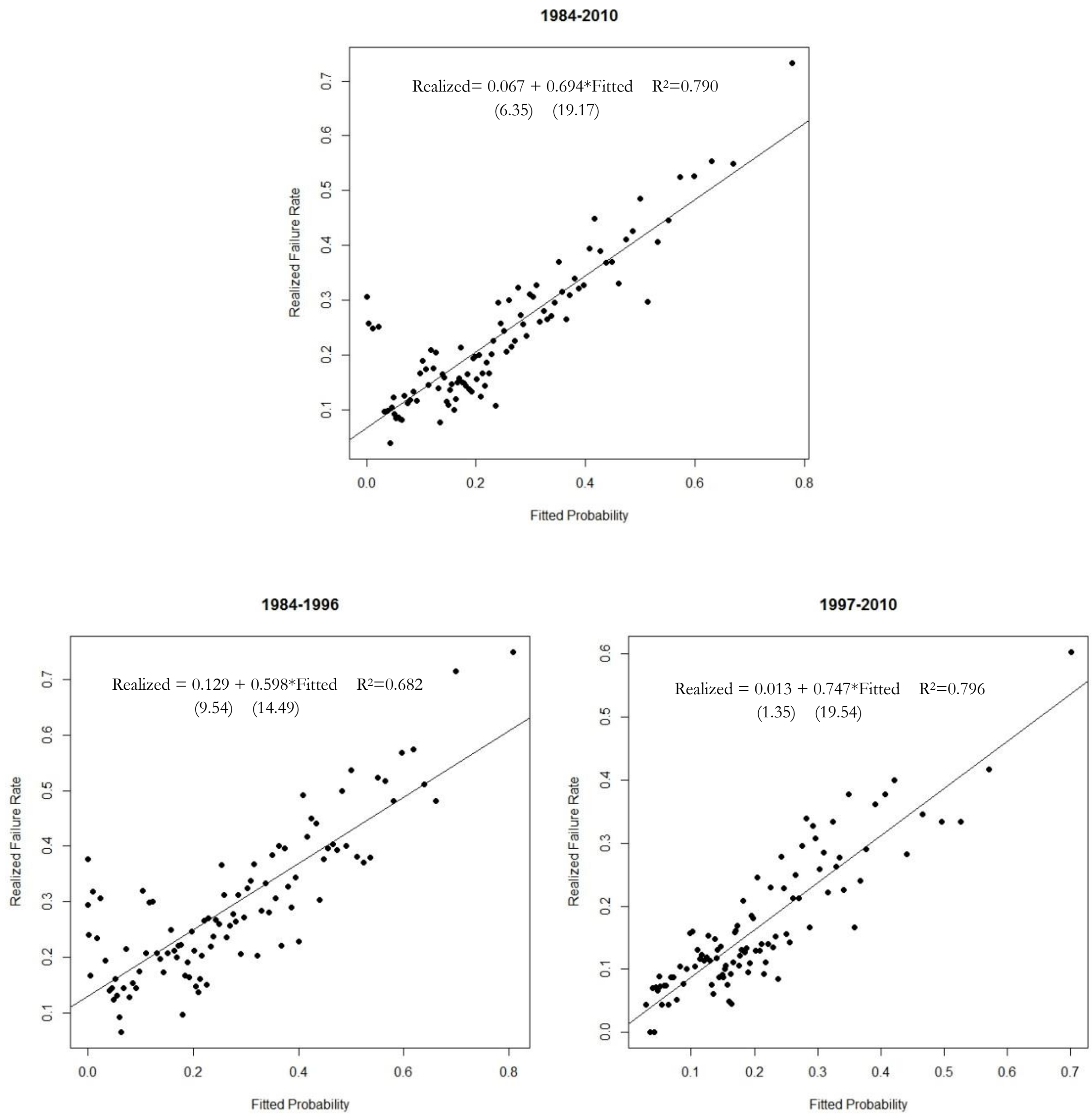

Figure 3. The ex-post failure rate: cross-sectional

This figure shows the cross sectional analysis on model accuracy by comparing predicted failure probability with the realized failure rate. The three figures show the analysis for the whole sample period (1984-2010), the first sub-period (1984-1996), and the second sub-period (1997-2010). I first sort all the deals into 100 equal-sized binds by the predicted failure probability (fitted probability). The x-axis of figures in Panel A is the average predicted failure probability and the y-axis is the realized failure rate. Predicted failure probability is modelled based on model (6) in Table 2. Realized failure rate is calculated as: number of deals withdrawn/(number of deals withdrawn + number of deals completed).

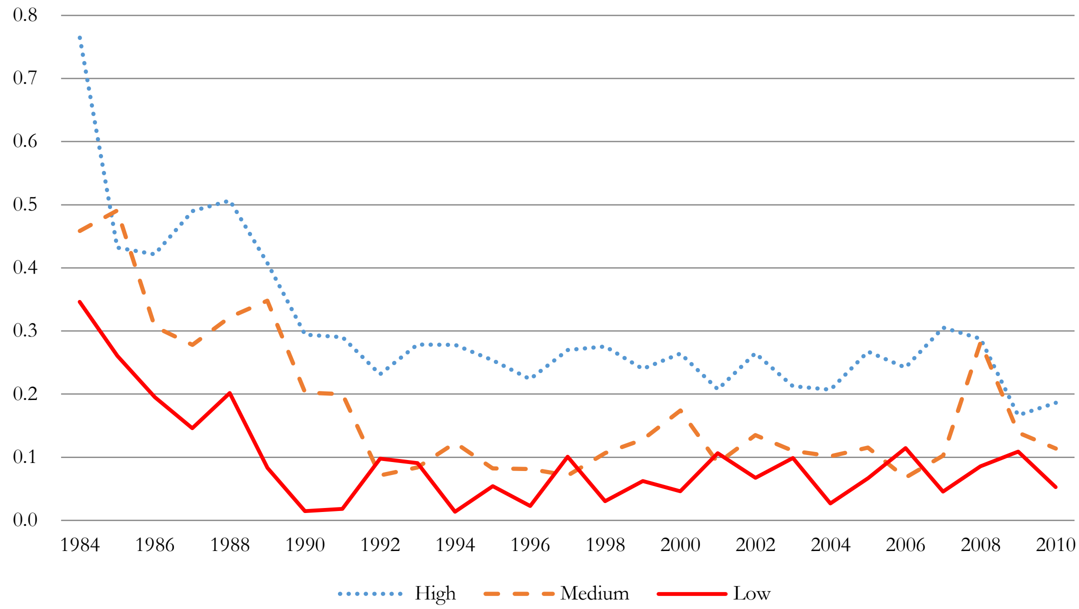

Figure 4. The ex-post failure rate: time series

This figure shows the time series analysis on model accuracy for three groups of deals with different value of ex-ante failure probabilities. Ex-ante failure probability is modelled based on model (6) in Table 2. Low, Medium and High indicate the deals with failure probability lower than 10%, between 10% and 20%, and others, respectively. The ex-post failure rate is calculated as number of deals withdrawn/(number of deals withdrawn + number of deals completed). The total number of deals is 16,163 and the sample period is from January 1984 to December 2010. Ex-post failure rate is calculated as number of deals withdrawn/ (number of deals withdrawn + number of deals completed).

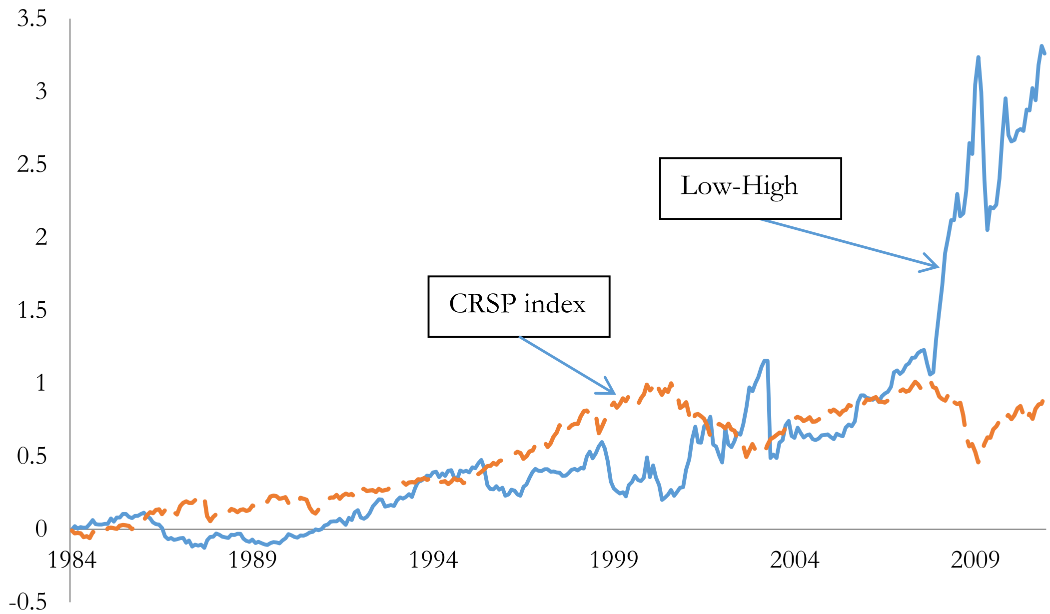

Figure 5. The Low-High portfolio

This figure shows the cumulative return of the Low-High portfolio from January 1984 to December 2010. The solid line represents the Low-High portfolio and the dashed line represents the CRSP value weighted index. Low and High indicate the deals with failure probability lower than 10%, and deals with failure probability higher than 20%, respectively. The deal failure probability is modelled based model (6) of Table 2. For each portfolio of stocks, I begin to hold a stock 2 trading days after deal announcement and until the deal resolution or 180 days after deal announcement. I calculate value weighted portfolio return and form a calendar portfolio. The Low-High portfolio is the difference between Low and High.

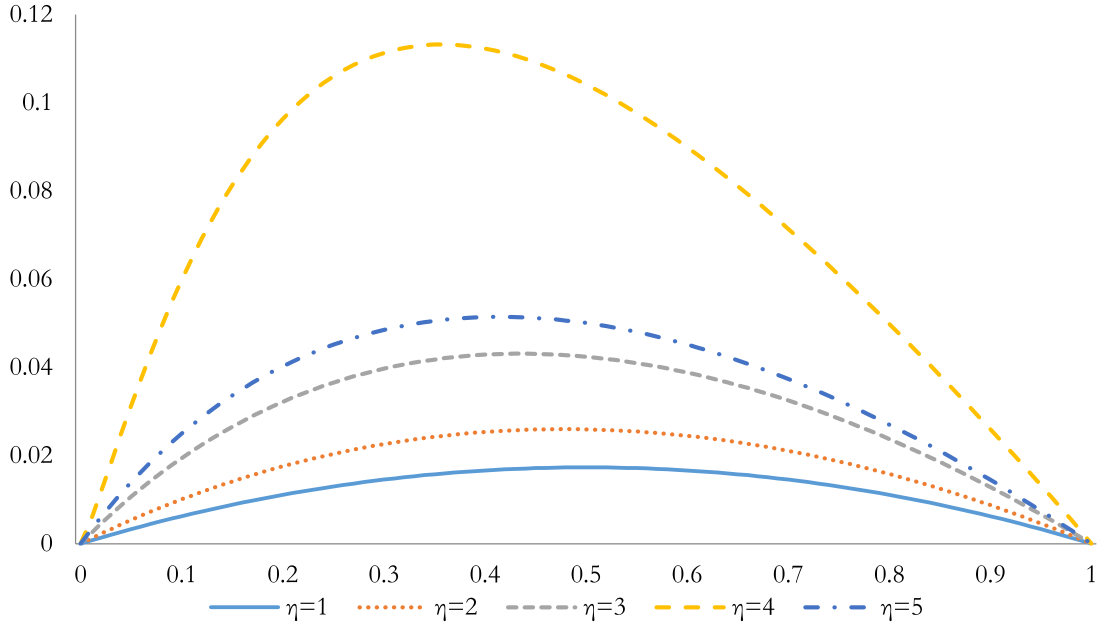

Figure 6. Expected Target Stock Returns under CRRA utility
This figure shows the expected target stock returns (modelled as in Figure 1) when for CRRA utility: UCRRA=-C$^{1-\eta}$. I report the results for five different values of η. I set P_{offer}=1.3 and P_{alone}=1.

Appendix.

Part I. Proof of equation (2)

Theories with probability weighting predicts that:

$$P=w^*(\pi)\ P_{alone}+w^*(1-\pi)\ P_{offer}, \qquad \text{(A1)}$$

where $w^*(\pi)$ is the decision weight investors put for deal failure and $w^*(1-\pi)$ is the decision weight investors put for deal success. In rank-dependent utility, $w^*(1-\pi)=1-w^*(\pi)$, but in cumulative prospect theory, $w^*(1-\pi)$ may not be equal to $1-w^*(\pi)$. It is easy to show that, in rank-dependent utility,

$$P=w^*(\pi)\ P_{alone}+(1-w^*(\pi))\ P_{offer}. \qquad \text{(A2)}$$

In cumulative prospect theory, the net utility gain of purchasing the target stock should be equal to 0. Assume that investors use the current target stock price (P) as the reference point, we have

$$0=w^*(\pi)\ (P-P_{alone}) + w^*(1-\pi)(P_{offer}-P). \qquad \text{(A3)}$$

Therefore,

$$P=\frac{w^*(\pi)}{w^*(\pi)+w^*(1-\pi)}P_{alone}+\frac{w^*(1-\pi)}{w^*(\pi)+w^*(1-\pi)}P_{offer}. \qquad \text{(A4)}$$

Now, we define

$$\begin{cases} w(\pi)=w^*(\pi), & \text{for rank-dependent utility;} \\ w(\pi)=\dfrac{w^*(\pi)}{w^*(\pi)+w^*(1-\pi)}, & \text{for cumulative prospect theory.} \end{cases}$$

Then equation (A1) can be rewritten as

$$P=w(\pi)\ P_{alone}+(1-w(\pi))\ P_{offer}, \qquad \text{(A5)}$$

which is the same as equation (2).

In both rank-dependent utility and cumulative prospect theory, $w^*(\pi)>\pi$ when π is small and $w^*(\pi)<=\pi$ when π is moderate or large. It is easy to prove that $w(\pi)>\pi$ when π is small and $w(\pi)<=\pi$ when π is moderate or large.

Part II. Calculation of the risk neutral moments

Bakshi, Kapadia, and Madan (2003) show that the risk neutral skewness is

$$RNSkew_{i,t}(\tau) = \frac{E_t^Q\left\{(R(t,\tau) - E_t^Q[R(t,\tau)])^3\right\}}{\left\{E_t^Q(R(t,\tau) - E_t^Q[R(t,\tau)])^2\right\}^{3/2}} = \frac{e^{r\tau}W_{i,t}(t,\tau) - 3\mu_{i,t}(t,\tau)e^{r\tau}V_{i,t}(t,\tau) + 2\mu_{i,t}(t,\tau)^3}{[e^{r\tau}V_{i,t}(t,\tau) - \mu_{i,t}(t,\tau)^2]^{3/2}}, \quad \text{(A6)}$$

where i, t, and τ represent stock, current time, and time to maturity, respectively. r is the risk free rate, $E_t^Q(.)$ is the expectation under the risk-neutral measure, $R(t,\tau)$ is the return from time t to $t+\tau$, and $\mu_{i,t}(t,\tau) = e^{r\tau} - 1 - \frac{e^{r\tau}}{2}V_{i,t}(t,\tau) - \frac{e^{r\tau}}{6}W_{i,t}(t,\tau) - \frac{e^{r\tau}}{24}X_{i,t}(t,\tau)$. Bakshi, Kapadia and Madan (2003) further show that, $V_{i,t}(t,\tau)$, $W_{i,t}(t,\tau)$ and $X_{i,t}(t,\tau)$ can be extracted from OTM options, and are defined as

$$V_{i,t}(t,\tau) = E_t^Q\left\{e^{-r\tau}R(t,\tau)^2\right\} = \int_{S(t)}^{\infty}\frac{2(1-\ln[K/S(t)]}{K^2}C(t,\tau;K)dK + \int_0^{S(t)}\frac{2(1+\ln[K/S(t)]}{K^2}P(t,\tau;K)dK, \quad \text{(A7)}$$

$$W_{i,t}(t,\tau) = E_t^Q\left\{e^{-r\tau}R(t,\tau)^3\right\} = \int_{S(t)}^{\infty}\frac{6\ln[K/S(t)] - 3(\ln[K/S(t)])^2}{K^2}C(t,\tau;K)dK - \int_0^{S(t)}\frac{6\ln[K/S(t)] + 3(\ln[K/S(t)])^2}{K^2}P(t,\tau;K)dK, \quad \text{(A8)}$$

$$X_{i,t}(t,\tau) = E_t^Q\left\{e^{-r\tau}R(t,\tau)^4\right\} = \int_{S(t)}^{\infty}\frac{12\ln[K/S(t)]^2 - 4(\ln[K/S(t)])^3}{K^2}C(t,\tau;K)dK + \int_0^{S(t)}\frac{12\ln[K/S(t)]^2 + 4(\ln[K/S(t)])^3}{K^2}P(t,\tau;K)dK. \quad \text{(A9)}$$

Ideally, $V_{i,t}(t,\tau)$, $W_{i,t}(t,\tau)$ and $X_{i,t}(t,\tau)$ should be calculated based on a continuum of European options with different strikes. However, in reality, only a limited number of options are available for each stock/expiration combination and individual equity options are not European. To accommodate the discreteness of options strikes, I follow Dennis and Mayhew (2002) to estimate the integrals in expressions (2) to (4) using discrete data.

Finally, I standardize risk neutral moments to 30 days by linearly interpolating the movements of the option with expiration closest to, but less than 30 days, and the option with expiration closest to, but greater than 30 days. If there is no option with maturity longer than 30 days (shorter than 30 days), I choose the longest (shortest) available maturity.

The data of options is from IvyDB's OptionMetrics database. IvyDB's OptionMetrics database provides data on option prices, volume, open interest, and Greeks for the period from January 1996 to December 2010. I include options on all securities classified as common stock. To minimize the impact of data errors, I remove options missing best bid or offer prices, as well as those with bid prices less than or equal to $0.05. I also remove options that violate arbitrage bounds, options with special settlement arrangement.[31] The mid-quote of the best bid and best offer is taken as the option price. I require at least two OTM puts and two OTM calls to calculate the risk neutral moments.

[31] OptionMetrics defines an option as having a standard settlement if 100 shares of the underlying security are to be delivered at exercise and the strike price and premium multipliers are $100 per tick. For options with a non-standard settlement, the number of shares to be delivered may be different from 100, and additional securities and/or cash may be required.

Part III. The effects of revisions: 1984-2010

I report the frequency of revisions and the portfolio returns after excluding deals with revisions for the whole sample period from 1984 to 2010. From 1984 to 2010, I have 16,163 deals in total, of which 1,096 deals have offer price revised. 275 are revised down and 821 are revised up. Low, Medium and High have 3,233, 4,380 and 8,550 deals, respectively. 2.1%, 1.9% and 1.5% are revised down, and 5.3%, 4.7% and 5.2% are revised up for the three portfolios of deals. Conditional on downward revision, the average revision ratio (defined as final offer/initial offer-1) is -9.78%, -15.43% and -16.20% for Low, Medium and High, respectively. Conditional on upward revision, the average revision ratio is 17.95%, 17.92%, and 18.01%, respectively. The targets in the Low portfolio have higher downward revision probabilities, but conditional on downward revision, the revision ratio is lower. These targets also have higher upward revision probabilities. Similar to the analysis for the sub-sample from 1997 to 2010, the revision analysis does not reveal evidence that revisions favour my portfolios differentially. Still, I recalculate the portfolio returns by excluding the deals with offer price revision. The results in Panel A1 show that the five-factor alpha is 1.238%. Different from the results in the period from 1997 to 2010 where the Low-High portfolio alpha is slightly lower when excluding the revised offers, the Low-High portfolio alpha is slightly higher when excluding the revised offers (the alpha is 1.060% when we do not excluding the revised offers). But again, the change is not large. Overall, revisions seems to be a second order factor in affecting the Low-High portfolio returns.