Option Prices and the Probability of Success of Cash Mergers

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Abstract

We study both theoretically and empirically option prices on firms undergoing a cash merger offer. To estimate the merger's success probability, we use a Markov Chain Monte Carlo (MCMC) method using a state space representation of our model. Our estimated probability measure has significant predictive power for the merger outcome even after controlling for variables used in the merger literature. As predicted by the model, a graph of the target firm's implied volatility against the strike price has a kink at the offer price, and the kink's magnitude is proportional to the merger's success probability.

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1 Introduction

In recent years, it has been shown empirically that option prices do not appear to contain economically significant information about future stock prices beyond what is already contained in the current stock price (see, e.g., Muravyev, Pearson, and Broussard (2013)). However, when a firm undergoes a merger attempt, its options are known to become informative about the underlying stock (see, e.g., Cao, Chen, and Griffin (2005)). A natural explanation is that during merger attempts, the merger's probability of success can fluctuate, thus creating an additional source of uncertainty that can no longer be determined only by the underlying price, but that options can potentially capture.

In this paper, we take a rigorous look at this intuition, and propose a model of stock and option prices for firms that are the subject of a merger attempt. To reduce the complexity of the problem, we focus on *cash* mergers, in which the acquiring firm plans to pay for the target firm with cash. Thus, we can consider the cash offer price as given and focus only on the target firm. The model is perhaps the simplest extension of the Black and Scholes (1973, henceforth "BS") model adapted to cash mergers.

Specifically, we consider a cash merger in which the acquiring firm makes a cash offer to the target firm.[1] The deal is expected to complete (i.e., succeed or fail) by a deterministic date called the *effective date* of the merger. Thus, if the deal is successful by the effective date, the shareholders of the target firm receive the cash offer price, otherwise the target's stock price reverts to the *fallback price*, which is assumed to follow a log-normal distribution.[2] The *success probability* of the merger is also modeled as a stochastic process similar to a log-normal process but constrained to be between 0 and 1. As in the martingale approach to the BS formula, instead of using the actual success probability, we focus on the risk-neutral probability.[3]

We provide formulas for the target's stock price as well as for the price of European call options on the target. The formulas have a particularly simple form when the success

[1]In practice, the offer price is significantly higher than the target's pre-announcement stock price, yielding an average premium of about 35% in our sample.

[2]The fallback price reflects the value of the target firm based on fundamentals, but also based on other potential merger offers. The fallback price therefore should not be thought as some kind of fundamental price of the target company but simply as the price of that firm if the *current* deal fails.

[3]In the absence of time discounting, the risk-neutral probability is equal to the price at of a digital option that offers 1 if the deal is successful and 0 otherwise.

probability and the fallback price are uncorrelated, and when the option expiration date is larger than the merger effective date. In that case, the target stock price is a mixture of the offer price and fallback price with mixing weights given by the (risk-neutral) success probability of the merger. Similarly, the price of European options on the target is a mixture the price of (i) an option on the cash offer price that expires at the effective date, and (ii) the price of a call option on the fallback price.

A simple but stark implication of the model is that the implied volatility curve[4] for the target of a cash merger must exhibit a kink (i.e., difference in slopes) at the merger offer price, if the expiration date arrives after the effective date. Indeed, a call option on a cash amount (the offer price) pays either the difference between that amount and the strike price if this difference is positive, or pays zero if the difference is negative. Moreover, the magnitude of the kink (difference in slopes) is proportional to the success probability of the merger.

FIGURE 1 ABOUT HERE

We verify this implication by considering all cash mergers announced between January 1996 and December 2014 that have call options traded daily on the target firm. Figure 1 shows indeed a pronounced "volatility smile" pattern after a merger announcement. Furthermore, we show that the shape of the volatility curve depends crucially on the probability of success of the cash merger: the smile is more pronounced when the probability of success is higher. To illustrate this, Figure 1 shows the difference between the average merger volatility curve for cash mergers that eventually succeeded (which on average should have a higher success probability) and the average volatility curve for cash mergers that eventually failed (which on average should have a lower success probability). In addition, for the successful deals we notice a pronounced kink in the volatility curve that occurs when the option strike price is close to the target offer price. These findings are qualitatively the same whether as call option prices we use the end-of-day bid price, ask price, or bid-ask mid-quote. Figure 1 also shows that the "volatility smile" pattern appears only after the merger announcement date: before the

[4]The implied volatility curve is defined as the BS-implied volatility as a function of the call option's strike price, holding the expiration date constant.

announcement, the average volatility curve is essentially flat for all merger targets.[5]

FIGURE 2 ABOUT HERE

Our model also produces stochastic volatility for the underlying stock price. The advantage of our approach is that the stochastic volatility is not exogenously specified but arises endogenously as a function of the success probability and other variables in the model. Figure 2 shows the stark difference between the median at-the-money implied volatility for cash mergers that eventually succeeded versus the median implied volatility for cash mergers that eventually failed. In particular, when then merger is close to a successful completion, the implied volatility is low. Intuitively, when the merger is close to succeeding, the equity price is close to the fixed cash offer and thus has low volatility.

Next, we depart from the qualitative findings in Figures 1 and 2 and provide more quantitative tests of our model. These tests require estimating the success probability, and we choose a natural parametrization similar to a log-normal process with constant coefficients, but with an additional term in the denominator to ensure that the probability lies between 0 and 1. We obtain a state space representation of our model with two latent variables (the success probability and the fallback price), and at least two observed variables (the stock price and at least one call option price). Since the BS formula is non-linear in the stock price, we need a statistical technique that can deal with non-linear formulas and identify both the values of the latent variables and the parameters that govern the processes. We thus use the Markov Chain Monte Carlo (MCMC) method; see, e.g., Johannes and Polson (2003), or Jacquier, Johannes, and Polson (2007).

First, we test whether the success probability estimated by our method predicts the outcome of the merger beyond the variables commonly used in the merger literature (see, e.g., Dessaint, Golubov, and Volpin (2017)). We find that our measure is highly significant in predicting the merger outcome even after we control for a "naive" success probability measure (see, e.g., Brown and Raymond (1986)) that is computed based on how closely the current stock price is to the offer price, in comparison to the pre-announcement price.

[5]These results are robust to using the median instead of the mean, and including in the calculation only implied volatility curves with at least 5 or at least 10 nonempty moneyness values.

Second, we test more formally the model implication that the volatility curve observed in Figure 1 has a kink at the offer price, and that the size of the kink increases with the success probability. To do that, we examine the equivalent kink in the call option price. The model predicts that the magnitude of this kink, normalized by the time discount coefficient, is precisely equal to the success probability. A regression of the normalized kink on the estimated success probability supports the prediction, as the regression coefficient is close to 1. Remarkably, in our estimation procedure we use only one option each day, yet we match well the whole cross section of options for that day, as well as the magnitude of the kink.

Third, our model also predicts that the return volatility of the target is stochastic and is proportional to the failure probability. This is illustrated in Figure 2, which shows that when the success probability is closer to 1, the target's implied volatility is closer to 0. A formal regression test confirms this prediction, as well as several additional predictions.

Fourth, our model implies that the merger risk premium is proportional to the drift coefficient in the diffusion process for the success probability. This is noisy at the individual deal level, but over the whole sample the average merger risk premium is significantly positive, at an 122.05% annual rate.[6] One explanation for this large number is that betting on merger success is a leveraged, option-like bet on the market index. Indeed, Mitchell and Pulvino (2001) find that the performance of mutual funds involved in merger arbitrage (also called "risk arbitrage") is equivalent to writing put options on a market index. One can argue that the merger risk premium is too high to be justified by fundamentals. If this is the case, the merger risk premium should be expected to decrease over time, as the result of more investors taking bets on mergers. In agreement with this intuition, we find that over the last five years of our sample (January 2010 to December 2014) the average annual merger risk premium has decreased to 86.47%.

Fifth, we compare the model-implied option prices to the ones that arise from the BS formula, and we find that our formula performs significantly better for call prices: the average percentage error is 9.39% for our model compared to an error of 19.49% in

[6]Dukes, Frolich and Ma (1992) consider the 761 cash mergers between 1971 and 1985 and report returns to merger arbitrage of approximately 0.47% daily, or approximately 118% annualized. See also Jindra and Walkling (2004), who obtain similar numbers but also take into account transaction costs.

the case of the BS model. In both cases, the error is larger than the average percentage bid-ask spread for options in our sample, which is 27.46%. In the same cross-section of firms, the 95% quartile of the percentage error for our model is 27.69%, compared to 68.61% for the BS model.

Our paper is, to our knowledge, the first to study option pricing on mergers by allowing the success probability to be stochastic. This has the advantage of being realistic. Indeed, many news stories before the resolution of a merger involve the success of the merger. A practical advantage is that by estimating the whole time series of success probabilities, we can estimate for instance the merger risk premium. Also, our model is well suited to study cash mergers, which are difficult to analyze with other models of option pricing. Subramanian (2004) proposes a jump model of option prices on *stock-for-stock* mergers. According to his model, initially the price of each company involved in a merger follows a process associated to the success state, but may jump later at some Poisson rate to the process associated to the failure state.[7] This approach cannot be extended to cash mergers: when the deal is successful, the stock price of the target becomes equal to the cash offer, which is essentially constant; thus, the corresponding process has no volatility. In our model, the price of the target is volatile: this is due to both a stochastic success probability and a stochastic fallback price.

The literature on option pricing for companies involved in mergers is scarce, and, with the exception of Subramanian (2004), mostly on the empirical side; see Barone-Adesi, Brown, and Harlow (1994) and Samuelson and Rosenthal (1986).[8] The latter paper is close in spirit to ours. They start with an empirical formula similar to our theoretical result, although they do not distinguish between risk-neutral and actual probabilities. Assuming that the success probability and fallback prices are constant (at least on some time-intervals), they develop an econometric method of estimating the success probabil-

[7] An implication of Subramanian (2004) is that the prices of the acquirer and the target companies are perfectly correlated, which is not realistic when the merger has a low success probability. Moreover, his model implies that the success probability of a merger decreases deterministically with time, even when the merger is likely to succeed. Samuelson and Rosenthal (1986) find empirically that the success probability usually increases over time.

[8] Several papers show that options can be useful for extracting information about mergers, although the variable of interest in many of these paper are the merger synergies; see Hietala, Kaplan, and Robinson (2003), Barraclough, Robinson, Smith, and Whaley (2013). Cao, Chen, and Griffin (2005) observe that option trading volume imbalances are informative prior to merger announcements, but not in general.

ity.[9] The conclusion is that market prices usually reflect well the uncertainties involved, and that the market's predictions of the success probability improve monotonically with time.

A related literature studies the volatility smile (or smirk, or sneer), a pattern in which at-the-money call options have lower implied volatilities than in-the-money or out-of-the-money options.[10] For European options on S&P 500 futures, Rubinstein (1994) and Jackwerth and Rubinstein (1996) show that the volatility smile became economically significant only after the 1987 market crash.[11] If changes in the probability of a stock index crash can affect the volatility smile, then one would expect certain extreme events in the life of a firm to also affect the volatility smile. A natural candidate for an extreme event is the firm being the target of a merger attempt. Compared with market crashes, mergers have the advantage that many of the variables involved are observable, e.g., the offer price and the effective date.

Our paper is also related to the literature on pricing derivative securities under credit risk. The similarity with our framework lies in that the processes related to the underlying default are modeled explicitly, and their estimation is central in pricing the credit risk securities. See, e.g., Duffie and Singleton (1997), Pan and Singleton (2008), Berndt, Douglas, Duffie, Ferguson, and Schranz (2005). Similar ideas to ours, but involving earning announcements can be found in Dubinsky and Johannes (2005), who use options to extract information regarding earnings announcements.

The paper is organized as follows. Section 2 introduces the theoretical model and derives our main pricing formulas, both for share prices and option prices corresponding to the stocks involved in a cash merger. Section 3 presents the data and methodology. Section 4 performs various empirical tests of our model. Section 5 discusses the assumptions of the model and the robustness of our empirical results. Section 6 concludes. All

[9]Samuelson and Rosenthal (1986) estimate the fallback price by fitting a regression on a sample of failed deals between 1976 and 1981. The regression is of the fallback price on the offer price and on the price before the deal is announced.

[10]Black and Scholes (1973) assume that the stock price follows a log-normal distribution with constant volatility, and thus the implied volatility is constant with respect to the option's strike price.

[11]The volatility smile is present in many other option markets, e.g., for options on currencies or fixed income securities. Several explanations have been proposed for the volatility smile, including stochastic volatility or jumps in the underlying prices, fear of crashes, etc.; see, e.g., Hull and White (1987), Heston (1993), Jackwerth and Rubinstein (1996), Bakshi, Cao, and Chen (1997), Duffie, Pan, and Singleton (2000), Jackwerth (2000), Kou (2002), Ziegler (2007), and Yan (2011).

proofs are in Appendix A.

2 Model

2.1 Setup

We use a continuous-time framework as in Part II of Duffie (2001). Let $W(t)$ be a 3-dimensional standard Brownian motion on a probability space $(\Omega, \mathcal{F}, P)$. The market has a risk-free security with instantaneous rate r, and three risky securities: B_1, the *offer price*; B_2, the *fallback price*; and p_m, the *bet price*, where the bet is placed on the success of the merger. Consider $T_e > 0$, the *effective date* of the merger. Then the prices of the three risky securities are Itô processes that satisfy for all $t \in [0, T_e)$,

$$\begin{aligned} \mathrm{d}B_i(t) &= \mu_i\big(B_i(t), t\big)\mathrm{d}t + \sigma_i\big(B_i(t), t\big)\mathrm{d}W_i(t), \quad i = 1, 2, \\ \mathrm{d}p_m(t) &= \mu_3\big(p_m(t), t\big)\mathrm{d}t + \sigma_3\big(p_m(t), t\big)\mathrm{d}W_3(t), \end{aligned} \tag{1}$$

such that μ_i and σ_i satisfy regularity conditions as in Duffie (2001), and the inequalities $B_i > 0$ and $p_m \in (0, 1)$ are satisfied almost surely. With this specification, the processes B_1, B_2 and p_m are independent. The case when some of these processes are correlated is discussed in Appendix C.

To model cash mergers, consider a company A (the acquirer) which announces at $t = 0$ that it wants to merge with a company B (the target). The acquisition is to be made with the cash amount B_1 per share, a quantity not necessarily known at $t = 0$. At the end of the effective date T_e, the public knows whether the merger succeeds or fails, and observes the actual offer price B_1 and fallback price B_2.[12] If the merger succeeds, B_1 is the cash amount that the target's shareholders receive per share. If the merger fails, the target remains an independent firm with price B_2.

At each date t between 0 and T_e, $p_m(t)$ is the price of a contract that pays 1 if the merger succeeds or 0 if the merger fails.[13] Define the *risk-neutral success probability*, or

[12] In this section, the effective date is assumed fixed and known in advance by all market participants. Later, in Appendix B we analyze the case when T_e can change before the deal is completed.

[13] In practice, this type of contract exists in betting markets that wager on the outcome of political elections or sports games, but, to our knowledge, not on mergers (probably because it would create opportunities for illegal insider trading). Even if this contract is not actually traded, we consider p_m

in short the *success probability*, to be the process:

$$q(t) \;=\; p_m(t)\; \mathrm{e}^{r(T_e - t)}\,. \tag{2}$$

Despite using continuous processes, we do not require the success probability on the effective date to converge either to 0 or 1. We thus allow for the possibility of a last-minute surprise at the effective date.[14] We define the time T_e' to be the instant after T_e when the uncertainty is resolved. We extend q at T_e' as follows: $q(T_e') = 1$ if the merger is successful, or $q(T_e') = 0$ if the merger fails. We extend B_1 and B_2 at T_e' by continuity: $B_i(T_e') = B_i(T_e)$ for $i = 1, 2$.

Let Q be the equivalent martingale measure associated to B_1 B_2 and p_m, such that these processes are Q-martingales after discounting at the risk-free rate r; see Chapter 6 in Duffie (2001).[15] Equation (2) implies that the success probability q is a Q-martingale. To include the final resolution of uncertainty, we extend the probability space Ω on which Q is defined by including the binomial jump of q at T_e'. This defines a new equivalent martingale measure Q' and a new filtration $\mathcal{F}'$ such that B_1, B_2, and q are processes on $[0, T_e] \cup \{T_e'\}$, and q is a Q'-martingale.

2.2 Option Prices and the Volatility Smile

In this subsection, we compute the stock price of the target company and the price of a European call option traded on the target with strike price K and expiration T after the effective date T_e (i.e., $T \geq T_e$).[16] Recall that $B_i(t)$, $i = 1, 2$, is, respectively, the market

as the price of a contract "as if" it was traded. Note that we are in effect assuming that that there is a complete set of traded securities contingent on the uncertainty associated with cash merger deals. However, even if markets are incomplete, there is a set of equivalent martingale measures such that the discounted prices of traded securities are martingales. Then, the actual market can be viewed as picking one measure from this set, and our estimation approach essentially infers what this measure is using data on stock and option prices. We thank an anonymous referee for making this point.

[14] One possibility is to model q as a process with jumps, but to estimate the jump parameters we would need a longer time series than we typically have for merger deals. Hence, we allow only one jump, at T_e. In practice, mergers are often decided before the effective date, and as a result in some cases the target stops trading before the effective date (in about 3% of the merger deals in our sample). In that case, in our empirical analysis we redefine the effective date as the last actual trading date. We discuss the issue of a random effective date in Appendix B.

[15] The equivalent martingale measure is associated to fairly general processes, and it is not to be confused with the BS risk-neutral probability.

[16] The complementary case $T < T_e$ is discussed in Appendix B.

price of a security that pays $B_i(T_e)$ on the effective date, where $B_1(T_e)$ is the offer price and $B_2(T_e)$ is the fallback price. If the call's owner receives receives cash before the expiration date (i.e., if the merger is successful and the offer price B_1 is above the strike K), the cash is invested a money market account with the risk-free rate r.

Denote by $C_i^{K,\tau}(t)$, $i = 1, 2$, the price of the European call option with strike K, expiration τ, and payoff at τ equal to:

$$\big(B_i(\tau) - K\big)_+ \;=\; \max\big\{B_i(\tau) - K, 0\big\}. \tag{3}$$

Proposition 1 provides formulas for the stock and option prices on the target firm.

Proposition 1. *If B_1, B_2, and q are independent processes, then the target's stock price satisfies:*

$$B(t) \;=\; q(t)B_1(t) + (1 - q(t))B_2(t), \quad t \in [0, T_e]. \tag{4}$$

The price of a European call option on B with strike K and expiration $T \geq T_e$ is:

$$C^{K,T}(t) \;=\; q(t)C_1^{K,T_e}(t) + (1 - q(t))C_2^{K,T}(t), \quad t \in [0, T_e]. \tag{5}$$

If it is not optimal to exercise American call options on B_1 and B_2 before expiration, then the same is true about B.

Thus, when the sources of merger uncertainty are uncorrelated, the target stock price has a particularly simple formula. The same is true for European option prices on the target if in addition the option expires *after* the effective date. If instead the option expires before the effective date, the formula is more involved (see Appendix B). When the sources of merger uncertainty are correlated, even the formula for the stock price becomes more complicated (see Appendix C).

In the rest of this subsection, we assume that B_1 is constant and B_2 follows a log-normal process:

$$\frac{\mathrm{d}B_2(t)}{B_2(t)} \;=\; \mu_2 \mathrm{d}t + \sigma_2 \mathrm{d}W_2(t). \tag{6}$$

Under these assumptions, American call options on B_1 and B_2 should not be exercised early, hence, according to Proposition 1, the same should be true for options on B.

Thus, American and European call options on B have the same price. Proposition 1 implies that the target stock price is:

$$B(t) \;=\; q(t)B_1\, \mathrm{e}^{-r(T_e-t)} + (1-q(t))B_2(t), \tag{7}$$

and the price of a call option on the target with strike K and expiration $T \geq T_e$ is:

$$C^{K,T}(t) \;=\; q(t)(B_1-K)_+\, \mathrm{e}^{-r(T_e-t)} + (1-q(t))C_2^{K,T}(t), \tag{8}$$

where $C_2^{K,T}(t)$ satisfies the BS equation:

$$\begin{aligned} C_2^{K,T}(t) \;&=\; C_{\mathrm{BS}}\big(B_2(t),K,r,T-t,\sigma_2\big) \;=\; B_2(t)\Phi(d_+) - K\, \mathrm{e}^{-r(T-t)}\, \Phi(d_-), \\ d_\pm \;&=\; \frac{\ln(B_2(t)/K) + \big(r \pm \frac{1}{2}\sigma_2^2\big)(T-t)}{\sigma_2\sqrt{T-t}}. \end{aligned} \tag{9}$$

We study the *volatility curve* of B, which is the BS-implied volatility as a function of the strike K. Corollary 1 shows that the volatility curve of the target firm B exhibits a kink at the offer price B_1, and provides a formula for the magnitude of the kink.

Corollary 1. *In the context of Proposition 1, suppose the offer price B_1 is constant and that B_2 is a log-normal process as in equation (6). Then, a European call option with strike K and expiration $T \geq T_e$ exhibits a kink at $K = B_1$ with magnitude:*

$$\left(\frac{\partial C}{\partial K}\right)_{K\downarrow B_1} - \left(\frac{\partial C}{\partial K}\right)_{K\uparrow B_1} \;=\; \mathrm{e}^{-r(T_e-t)}\, q(t). \tag{10}$$

The implied volatility also exhibits a kink at $K = B_1$ with magnitude:

$$\left(\frac{\partial \sigma_{\mathrm{impl}}}{\partial K}\right)_{K\downarrow B_1} - \left(\frac{\partial \sigma_{\mathrm{impl}}}{\partial K}\right)_{K\uparrow B_1} \;=\; \frac{\mathrm{e}^{-r(T_e-t)}\, q(t)}{\nu(B,K,r,\tau,\sigma_{\mathrm{impl}})}, \tag{11}$$

where $\nu = \frac{\partial C}{\partial \sigma}$ is the call option vega, and σ_{impl} is the BS-implied volatility. Moreover, for $q(t)$ sufficiently close to 1 and T_e sufficiently close to T, the slope $\left(\frac{\partial \sigma_{\mathrm{impl}}}{\partial K}\right)_{K\uparrow B_1}$ is negative and the slope $\left(\frac{\partial \sigma_{\mathrm{impl}}}{\partial K}\right)_{K\downarrow B_1}$ is positive.

Corollary 1 shows that the magnitude of the kink (the difference between the slope of the curve on the right and left of $K = B_1$) is equal to the time-discounted success probability, divided by the option vega. Moreover, the left slope is negative and the right slope is positive for most parameter values. Thus, a "volatility smile" arises naturally for options on cash mergers, in the form of a kink at the offer price $K = B_1$ (see also Figure 1).

Next, we show that the stock price computed in equation (7) exhibits stochastic volatility. We define the instantaneous volatility of a positive process $B(t)$ as the process $\sigma_B(t)$ that satisfies:

$$\frac{\mathrm{d}B(t)}{B(t)} = \mu_B(t)\mathrm{d}t + \sigma_B(t)\mathrm{d}W(t), \tag{12}$$

where $W(t)$ is a standard Brownian motion. To provide an explicit formula for the instantaneous volatility of B, we assume a specific process for the success probability:[17]

$$\frac{\mathrm{d}q(t)}{q(t)\big(1-q(t)\big)} = \mu_q\mathrm{d}t + \sigma_q\mathrm{d}W_q(t), \tag{13}$$

where μ_q and σ_q are constant, and $W_q(t)$ is a standard Brownian motion.

In Corollary 2, we compute the instantaneous volatility $\sigma_B(t)$ when the company B is the target of a cash merger.

Corollary 2. *Suppose B_1 is constant, $B_2(t)$ satisfies equation (6), and $q(t)$ satisfies equation (13), with W_2 and W_q uncorrelated. Then, the instantaneous volatility of B satisfies:*

$$\begin{aligned}\sigma_B(t) &= \big(1-q(t)\big)\left(\left(\frac{B(t)-B_2(t)}{B(t)}\,\sigma_q\right)^2 + \left(\frac{B_2(t)}{B(t)}\,\sigma_2\right)^2\right)^{1/2}\\ &= \big(1-q(t)\big)\,\frac{B_2(t)}{B(t)}\left(\left(\frac{B_1\,\mathrm{e}^{-(T_e-t)}-B_2(t)}{B_2(t)}q(t)\right)^2\sigma_q^2 + \sigma_2^2\right)^{1/2}.\end{aligned} \tag{14}$$

If $T_e = T$, the BS-implied volatility $\sigma_{\mathrm{impl}}(t)$ of a European call option on B with strike K and expiration T approaches 0 when $q(t)$ approaches 1.

One implication of Corollary 2 is that the instantaneous volatility of the target company B is proportional to the failure probability, $1-q$, a fact which we test empirically in Section 4.

[17] This is similar to a log-normal process but ensures that q always lies between 0 and 1.

When the merger is almost surely successful, i.e., when the success probability $q(t)$ approaches 1, the BS-implied volatility of the target company B approaches 0. Intuitively, when the success of the merger is almost assured, the stock price of the target equals the cash offer, which is assumed constant and hence has no volatility. This result is line with Figure 2, where the implied volatility of the target company B in a merger tends to be lower for merger deals that are eventually successful.

Corollary 2 implies that the volatility of the target company in a merger is naturally stochastic. This is not obtained simply by assumption as in other studies, but it is a result of a model which provides economic underpinnings for stochastic volatility.

3 Data and Methodology

3.1 Sample of Cash Mergers

We build a sample of all the cash mergers that were announced between January 1st, 1996 and December 31st, 2014, and have options traded on the target company. Merger data, e.g., company names, offer prices and effective dates, are from Thomson Reuters SDC Platinum. Option data are form OptionMetrics, which reports daily closing prices starting from January 1996. We use OptionMetrics also for daily closing stock prices, and for consistency we compare them with data from the Center for Research in Security Prices (CRSP).

To construct the sample, in SDC Platinum we search for all domestic mergers (deal type 1, 2, 3, 4, 11) with the following characteristics: *M&A Type* equal to "Disclosed Dollar Value"; target publicly traded; consideration offered in cash (category 35, 1) with *Consideration Structure* equal to "CASHO" (cash only); *Percent of Shares Acquiror is Seeking to Own after Transaction* between 80 and 100; *Percent of Shares Held at Announcement* less than 20 (including empty); *Status* either "Completed" or "Withdrawn".[18] This initial search produces 3298 deals. After removing deals with no option information in OptionMetrics before Announcement, there are 973 deals left. We fur-

[18] This condition is not too restrictive, since the deal announcement date must before December 31st, 2014, which should leave enough time for most mergers to be completed by October 27, 2016, the date of the SDC query.

ther remove the deals with 10 options or less traded while the merger is ongoing (12 deals) and deal period equal to two days or less (4 deals). After reading in detail the description of the mergers in this list, we further remove the deals for which (i) the offer is not pure cash (includes the acquirer's stock), and (ii) the target company is subject to another concurrent merger offer. There are 843 deals left, of which 736 were completed and 107 were withdrawn.

To create our final sample of mergers, we remove the deals for which we cannot run our estimation procedure, i.e., we remove the deals with: duration of four days or less (2 deals); at least one day with no underlying stock prices traded on the target (1 deal); at least one day with no options quoted (14 deals); no options quoted with expiration date past the current effective date of the merger (13 deals); non-converging estimation procedure (2 deals).[19] The final sample consists of 812 merger deals, of which 711 were completed and 101 were withdrawn.

As our estimation procedure depends on the offer price and the effective date, we need to find the deals during which either of these variables changed. To determine changes in the offer price, it is not enough to observe the SDC field *Price Per Share*, as this records only the last offer price. Therefore, we examine the following fields: *Consideration*, which gives a short list of offer prices; *Synopsis*, which describes this list in more detail; *History File Event* and *History File Date*, which together give a list of events including dates when the offer was sweetened (offer price went up) or amended (offer price changed, either up or down).

The effective date of a merger is defined by SDC as the date when the merger is completed or when the acquiring company officially stops pursuing the bid. To determine changes in effective date, we analyze the SDC field *Tender Offer Extensions* and then read the *History File Event* and *History File Date* to extract the dates at which the tender offer got extended (even if the number of tender offers is blank, we search for "effective" or "extended").[20]

[19]The non-convergence in these two cases comes from the scarcity of call option trades throughout the deal (the selection procedure is based on call option volume *before* the deal announcement). As a result, the call prices are almost constant (the quotes are stale) throughout the deal, and thus the estimation procedure fails to properly identify the state variables.

[20]Useful information is found in the fields *Tender Offer Original Expiration Date* (which is self-explanatory) or *Tender Offer Expiration Date* (which is the last effective date on record). The *History*

TABLE 1 ABOUT HERE

Table 1 shows summary statistics for our merger sample. E.g., the average deal duration (the number of trading days until the deal either succeeds or fails) is 67 days, while the maximum deal duration is 402 days. We define the *offer premium* as the percentage difference between the offer price and the target company stock price on the day before the merger announcement. The offer premium in our sample has a mean of 33.5% and a standard deviation of 37.5%. The offer price changes rarely in our sample: the median number of changes is 0 and the mean is well below 1 (it is equal to 0.13). Even the 95% percentile is 1 (one change for the duration of the deal), with a maximum of 5. The effective date changes more frequently in our sample, but the median is still 0 and the mean is still below 1.

Table 1 includes statistics about how often options are traded on the target company. The fraction of trading days when there exists at least one option with positive trading volume is 65% for the average deal, indicating that options in our sample are illiquid. Table 2 gives additional evidence that for the illiquidity of options. E.g., the average percentage bid-ask spread for all call options is 27.5%.

TABLE 2 ABOUT HERE

For stock prices we use closing daily prices and for option prices we use the closing bid-ask mid-quote, i.e., the average between closing ask and bid prices. For successful deals, the options traded on the target company are converted into the right to receive the cash difference between the offer price and the strike price, if this difference is positive, or 0 otherwise.

3.2 Methodology

For each cash merger in our sample, we record the following observed variables for the target company: the effective date of the merger T_e, measured as the number of trading

File Event field usually says what the new Effective Date is, but sometimes we guess it based on the following rule: if the effective date changes at a later date T without any current effective date being previously announced, we consider T as the earlier effective date. This assumption is reasonable, as in principle a current effective date should always be filed with the SEC.

days from the announcement, the risk-free interest rate r, the cash offer price B_1, the time series $B(t)$ of stock prices of the target company B on trading day t, and the time series $C^{K,T}(t)$ of call option prices traded on B with strike K and expiration T. When the offer price or effective date changes, we simply change the value of B_1 or T_e in the formula, thus essentially assuming that these changes are unanticipated.[21]

The latent variables in this model are the success probability $q(t)$ and the fallback price $B_2(t)$, which follow processes with constant coefficients and independent increments:

$$\frac{\mathrm{d}q(t)}{q(t)\big(1-q(t)\big)} = \mu_1 \mathrm{d}t + \sigma_1 \mathrm{d}W_1(t), \tag{15}$$

$$\frac{\mathrm{d}B_2(t)}{B_2(t)} = \mu_2\, \mathrm{d}t + \sigma_2\, \mathrm{d}W_2(t), \tag{16}$$

An alternative specification with correlated increments $\mathrm{d}W_1(t)$ and $\mathrm{d}W_2(t)$ is discussed in Appendix C.

As we need to consider a discrete state space model, we start counting from $t = 1$ instead of $t = 0$. Then, the notation $B(0)$ corresponds to the target's stock price one day before the announcement. At each date t, we consider only call options with expiration date T larger than the current merger effective date T_e. Proposition 1 implies that the stock price $B(t)$ and the call option price $C^{K,T}(t)$ satisfy equations (7) and (8), respectively. In our empirical methodology, we assume that these equation hold approximately:

$$B(t) = q(t)B_1\, \mathrm{e}^{-r(T_e-t)} + (1-q(t))B_2(t) + \varepsilon_B(t), \tag{17}$$

$$C^{K,T}(t) = q(t)(B_1-K)_+\, \mathrm{e}^{-r(T_e-t)} + (1-q(t))C_{\mathrm{BS}}(B_2(t), K, T-t) + \varepsilon_C(t), \tag{18}$$

where $C_{\mathrm{BS}}(S, K, T-t)$ satisfies the BS formula (9) with arguments r and σ_2 omitted, and the errors $\varepsilon_B(t)$ and $\varepsilon_C(t)$ are IID bivariate normal:

$$\begin{bmatrix} \varepsilon_B(t) \\ \varepsilon_C(t) \end{bmatrix} \sim \mathcal{N}(0, \Sigma_\varepsilon), \quad \text{where} \quad \Sigma_\varepsilon = \begin{bmatrix} \sigma^2_{\varepsilon,B} & 0 \\ 0 & \sigma^2_{\varepsilon,C} \end{bmatrix}. \tag{19}$$

[21] Table 1 shows that changes in B_1 and T_e are rare. Section 5 discusses these issues in more detail.

In the main empirical specification, on each day t we select only the option with maximum trading volume on that day.[22]

Equations (15), (16), (17), (18), and (19) define a discrete state space model with observables $B(t)$ and $C(t)$, latent (state) variables $q(t)$ and $B_2(t)$, and model parameters μ_1, σ_1, μ_2, σ_2, $\sigma_{\varepsilon,B}$, and $\sigma_{\varepsilon,C}$. We adopt a Bayesian approach and conduct inference by sampling from the joint posterior density of state variables and model parameters, given the observables.

Specifically, we use a Markov Chain Monte Carlo (MCMC) method based on a state space representation of our model. In this framework, the state equations (15) and (16) specify the dynamics of latent variables, while the pricing equations (17) and (18) specify the relationship between the latent variables and the observables. The addition of errors in the pricing equations, with the distribution described by equation (19), is standard practice in state space modeling; it also allows us to extend the estimation procedure to multiple options and missing data. This approach is one of several (Bayesian or frequentist) suitable approaches for this problem and is not new to our paper. For a discussion, see, e.g., Johannes and Polson (2003), or Koop (2003). The resulting estimation procedure is described in detail in Appendix D.[23] All priors used in our estimation are flat.

4 Empirical Results

In this section, we perform various tests of our theoretical model and verify whether the estimated success probability predicts merger outcomes. Furthermore, we compare the pricing errors in our model with those in the standard BS model.

[22]If all option trading volumes are zero on that day, use the option with the strike K closest to the strike for the most currently traded option with maximum volume. Finally, if none of these criteria are met, we simply choose the at-the-money option on that day.

[23]As noted by Johannes and Polson (2003), equations of the type (17) or (18) are a non-linear filter. The problem is that it is difficult to do the estimation using the actual filter. Instead MCMC is a much cleaner estimation technique, but it does smoothing, as it uses all the data at once.

4.1 Success Probabilities

From our sample of 812 cash mergers announced between 1996 and 2014, Table 3 shows information for 10 merger deals sorted on the offer value: the five largest deals that succeeded and five largest deals that failed.[24]

TABLE 3 ABOUT HERE

For the 10 deals in Table 3, we show in Figure 3 the time series of the median estimated success probability q, as well as a 90% credibility interval, i.e., we show the 5th and 95th percentiles of the posterior distribution of q produced by our MCMC method.[25] Figure 3 shows that the estimated success probabilities for the five deals that succeeded (on the left column) are overall much higher than for the five deals that failed (on the right column).

FIGURE 3 ABOUT HERE

In Table 4, we generalize these results to the whole cash merger sample, by verifying whether the deal's success or failure is predicted by our estimated success probability.[26] For comparison, we use the "naive" success probability measure:

$$q^{\text{naive}}(t) \;=\; \frac{B(t) - B(0)}{B_1 - B(0)}, \quad \text{if } B(0) < B(t) < B_1, \tag{20}$$

where B_1 is the offer price, $B(0)$ is the target company's stock price one day before the announcement, and $B(t)$ is the target company's stock price at date t.[27] The naive measure is used widely in the merger literature; see, e.g, Brown and Raymond (1986). It essentially sets the fallback price equal to the pre-announcement price, $B(0)$, while our method estimates a separate fallback price, $B_2(t)$.

[24]The offer value is defined as the offer price multiplied by the target's number of shares outstanding.

[25]Figure 3 is the only place in this paper when we use all the available options for our estimation method. If instead we select only one option each day (the call with the maximum trading volume on that day), then the results still hold but the error bars are wider and the contrast between the two groups is not as strong.

[26]Recall that q is the risk-neutral probability, not the physical probability. Therefore, the coefficient estimates in Table 4 may be biased unless the two probabilities coincide, which could be the case if, e.g., the risk regarding the outcome of a merger deal is idiosyncratic.

[27]If $B(t)$ is close to the offer price B_1, $q^{\text{naive}}(t)$ is high. If $B(t)$ is close to the pre-announcement stock price $B(0)$, $q^{\text{naive}}(t)$ is low.

TABLE 4 ABOUT HERE

Table 4 shows the results of probit regressions of the deal outcome (a dummy variable equal to 1 if the deal is successful or 0 otherwise) on the average values of q or q^{naive} over the period when the merger deal is outgoing, while controlling for variables used in the merger literature.[28]

Our success probability measure has significant predictive power for the deal outcome, even after controlling for the naive measure. When running separately the probit regressions, the pseudo-R^2 increases from 25.39% for the naive measure to 46.45% for our measure if we do not use any controls, or from 43.72% to 57.25% if we use controls and year fixed effects. If we only average the success probability measures during the second half of the deal period, the pseudo-R^2 increases from 33.01% for the naive measure to 53.31% for our measure when there are no controls, or from 49.63% to 64.78% if we use controls and year fixed effects.[29] When running the probit regression on both q and q^{naive}, we see that our measure has a higher z-statistic. However, the naive success probability remains significant, which indicates that it still contains information relevant to the deal's success that our measure does not capture.

4.2 Call Price Kink and Volatility Kink

As shown theoretically in Section 2, the price of a call option on the target company in a cash merger deal has a kink at the offer price, and so does the implied volatility curve (see Corollary 1). We illustrate the implied volatility kink by selecting the deal with the largest offer premium (75.44%) among the 10 large cash merger deals in Table 3.[30] The target company of this deal is AT&T Wireless, with ticker AWE.

FIGURE 4 ABOUT HERE

[28]See, e.g., Dessaint, Golubov, and Volpin (2017). Controlling for valuation measures, e.g., the total assets or the net income of the acquirer and the target companies produces very similar results, but the sample is reduced to almost half. We do not report these results for brevity, but they are available from the authors upon request.

[29]For brevity, we do not report the results when the averages are taken for the second half of the deal period, but these results are available from the authors upon request.

[30]The offer premium is defined as the ratio $\big(B_1 - B(0)\big)/B(0)$, where B_1 is the offer price and $B(0)$ is the target's stock price one trading day before the merger announcement date. For two target companies in our sample, the price one day before the merger announcement is missing, and therefore the offer premium is also missing.

Figure 4 shows that our model fits well not only the volatility kink for AWE but the whole implied volatility curve. This is remarkable, as our estimation method only uses one option per day, yet the model is capable of accurately predicting the whole cross section of call prices for each day. Moreover, as the deal is becoming closer to completion (and the success probability is likely to increase), the kink is also increasing. This fact is predicted by Corollary 1, which implies that the magnitude of the call price kink (i.e., the slope difference in call price above and below the strike) should be equal to the success probability normalized by the time discount coefficient.

In Table 5, we test the aforementioned equality by running panel regressions of the target's call price kink $C^{\text{kink}}(t)$ on the deal's normalized success probability $q_{\text{norm}}(t) = q(t)\,\mathrm{e}^{-r(T_e-t)}$, where the risk-free rate r is extracted from the yield curve by interpolation. Theoretically, the regression coefficient should be equal to 1, but as the independent variable q is estimated with noise, the errors-in-variables (EIV) problem implies that the regression coefficient should be smaller than 1.

TABLE 5 ABOUT HERE

To make the distributions of the dependent and independent variables closer to the normal distribution, we also regress a modified kink $\tilde{C}^{\text{kink}}$ on a modified normalized success probability $\tilde{q}_{\text{norm}}(t)$, where the modification involves truncating the values of the kink to be in $(0,1)$ and inverting them via the standard normal cumulative density function to be a variable on the whole real line. If we want to use time fixed effects, one problem is that there is usually no overlap between the time periods when two different merger deals are ongoing. Nevertheless, there might be still time trends that can occur during the lifetime of the deal, which means that using fixed effects in the regression would be useful. Therefore, for each deal, we divide the period between the merger announcement date (denoted by $t = 1$) and the effective date (denoted by $t = T_e$) into 10 periods. Namely, for each date $t = 1, \dots, T_e$, we define its corresponding period by $\lceil 10t/T_e \rceil$, where $\lceil x \rceil$ denotes the (integer) ceiling of the real number x. We then use time fixed effects at the period level, and cluster standard errors by firm (clustering by firm and time produces very similar results).

As the model predicts, Table 5 confirms that there is a positive relation between the call price kink and the success probability. The coefficient on the success probability is between 0 and 1, and significant in all specifications. The constant coefficient is statistically significant, indicating that there is a positive bias in estimating the call price kink. Indeed, as observed in Figure 4, when one estimates a linear kink with concave price curves above and below $K = B_1$, the estimated kink is larger than the actual kink.[31]

4.3 Target Volatility

In Section 2, we show that the return volatility of the target company in a cash merger, $\sigma_B(t)$, is proportional to the failure probability, $1 - q(t)$ (see Corollary 2). To test this result, we need to estimate a time-varying return volatility, which could be done using GARCH or one of the related models. However, to avoid parametric assumptions, we divide the time between the announcement date ($t = 1$) and the effective date ($t = T_e$) in five periods, and estimate a return standard deviation for each period.[32] Let $\tau = \lfloor T_e/5 \rfloor$, where $\lfloor x \rfloor$ denotes the (integer) floor of the real number x. The five intervals are: $I_1 = [1, \tau]$, $I_2 = [\tau + 1, 2\tau]$, $I_3 = [2\tau + 1, 3\tau]$, $I_4 = [3\tau + 1, 4\tau]$, and $I_5 = [4\tau + 1, T_e]$. For each target company and each period (time interval) $k = 1, \ldots, 5$, we construct the return volatility $\sigma_{B,k}$ as the return standard deviation over I_k, and the success probability q_k as the average success probability over the interval I_k. Thus, in an OLS regression of the target's return volatility on the deal's failure probability, the slope coefficient should be positive.

TABLE 6 ABOUT HERE

We test this prediction in Table 6 Panel A. We use firm and time fixed effects, and standard errors are clustered by firm (clustering by firm and time produces very similar results). As the model predicts, the coefficient of the failure probability is positive and highly significant in all regression specifications.

[31] To reduce this bias, one can estimate the kink using a spline approximation rather than linear. However, this method requires two additional options (one with $K > B_1$ and one with $K < B_1$), which severely reduces the sample.

[32] In Table 6, we use five periods rather than 10 (as in Table 5), as we do not have estimates of the independent variable at each date but rather must estimate the return volatility over each period.

By visual inspection of equation (14), we obtain additional implications of Corollary 2. First, deals with higher q-volatility σ_q and higher fallback volatility σ_2 tend to have targets with higher return volatility $\sigma_{_B}$. Second, deals with a higher offer premium $\big(B_1 - B(0)\big)/B(0)$ tend to have higher $\sigma_{_B}$. Indeed, a higher offer premium suggests a higher term $\big(B_1\,\mathrm{e}^{-r(T_e-t)} - B_2(t)\big)/B_2(t)$ in equation (14), hence a higher $\sigma_{_B}$, as long as the fallback price $B_2(t)$ does not stray too far from the pre-announcement price $B(0)$. To test these predictions, we note that some independent variables are constant across time, and thus we run cross-sectional regressions in which we collapse the variable q along its mean and estimate $\sigma_{_B}$ as the standard deviation of the whole return time series of $B(t)$. As the terms in equation (14) appear multiplicatively, we use as dependent variable the natural logarithm of $\sigma_{_B}$.

Table 6 Panel B confirms our predictions, except that in one specification the offer premium $\big(B_1 - B(0)\big)/B(0)$ has the wrong sign. A possible explanation is that the positive effect of the offer premium depends on how close the fallback price $B_2(t)$ is to $B(0)$. This identification is sensitive in the fallback volatility parameter σ_2, especially since by running cross-sectional regressions, we average out $\sigma_{_B}$ across the time dimension. Table 6 shows that indeed the coefficient on the offer premium is positive if we omit σ_2 from the regressions.

By comparing the regressions in Panels A and B, note that in Panel A a large increase in R^2 comes from introducing the firm fixed effects, while in Panel B a similar increase in R^2 comes from controlling for the (constant) estimates of σ_q and σ_2 across firms. This suggests that the firm fixed effects are driven largely by these volatility estimates.

4.4 Merger Risk Premium

In this subsection, we estimate the merger risk premium from the specification (15) for the success probability: $\mathrm{d}q/\big(q(1-q)\big) = \mu_1 \mathrm{d}t + \sigma_1 \mathrm{d}W_1$. In general, for a price process with $\mathrm{d}S/S = \mu(S,t)\mathrm{d}t + \sigma(S,t)\mathrm{d}W(t)$, the instantaneous risk premium is $\mathsf{E}_t(\mathrm{d}S/S) - r\mathrm{d}t = (\mu(S,t) - r)\mathrm{d}t$. For a merger, its risk premium is associated to the price $p_m(t) = q(t)\,\mathrm{e}^{-r(T_e-t)}$ of a digital option that pays 1 if the merger is successful and 0 otherwise.

Thus, the instantaneous merger risk premium is:[33]

$$\mathsf{E}_t\left(\frac{\mathrm{d}p_m}{p_m}\right) - r\mathrm{d}t \;=\; \mathsf{E}_t\left(\frac{\mathrm{d}q}{q}\right) \;=\; (1-q)\mu_1\mathrm{d}t. \tag{21}$$

By averaging the merger risk premium over the life of the deal, the deal's average risk premium is equal to $(1-\bar{q})\mu_1$. Empirically, the individual estimates are very noisy, but over the whole sample the average merger risk premium is significantly positive, and the annual figure is 122.05%. This number is very large but consistent with the existing literature.[34] One potential explanation for the large estimate is that merger arbitrage (which is also called "risk arbitrage") is a leveraged, option-like bet on the market index (see Mitchell and Pulvino (2001)). However, it is possible that the merger risk premium is too high to be justified by fundamentals. In that case, it is likely that over time investors have entered the merger arbitrage business and by their entry have brought down the risk premium. To see whether this is the case, we restrict to the last five years of our merger sample, with announcement date is between January 2010 and December 2014. For this subsample, the estimated premium is 86.47%, which is indeed significantly lower than for the whole sample.

4.5 Pricing Errors

In this subsection, we investigate the performance of the pricing formula (7) for the target stock price $B(t)$ and the formula (8) for the call option price $C(t)$, which hold with errors $\varepsilon_B(t)$ and $\varepsilon_C(t)$, respectively. We denote with a hat the fitted values for the stock price, $\hat{B}(t)$, and the call option price, $\hat{C}(t)$. Table 7 shows summary statistics for the average stock pricing error $1/T_e \times \sum_{t=1}^{T_e} \left|\big(\hat{B}(t) - B(t)\big)/B(t)\right|$ over the duration of the deal. The stock pricing errors are in general very small, with a median error of 3.2 basis points.

TABLE 7 ABOUT HERE

[33]Equation (21) implies that the merger risk premium is near 0 when q is near 1. This comes from the functional specification of q in (15), which implies that $\mathrm{d}q/q$ has almost zero volatility (and hence it is almost risk-free) when q approaches 1.

[34]Dukes, Frolich and Ma (1992) find an average daily premium of 0.47% (ca. 118% annualized) for 761 cash mergers between 1971 and 1985. Jindra and Walkling (2004) confirm the results for cash mergers but also take into account transaction costs.

Table 8 shows the percentage errors in call option prices computed according to two models: "BMR," which denotes the model in this paper, and "BS," which denotes the Black and Scholes (1973) model with volatility parameter $\sigma = \bar{\sigma}_{ATM}$, the average implied volatility for the at-the-money (ATM) call options on the target company over the duration of the deal.

TABLE 8 ABOUT HERE

The error is computed by restricting the sample of call options according to the moneyness of the option, i.e., the ratio of the strike K to the underlying stock price $B(t)$. We consider the following moneyness categories: all call options; deep-in-the-money (Deep-ITM) calls, with $K/B < 0.9$; in-the-money (ITM) calls, with $K/B \in [0.9, 0.95)$; near-in-the-money (Near-ITM) calls, with $K/B \in [0.95, 1]$; near-out-the-money (Near-OTM) calls, with $K/B \in [1, 1.05)$; out-of-the-money (OTM) calls, with $K/B \in [1.05, 1.1]$; and deep-out-of-the-money (Deep-OTM) calls, with $K/B > 1.1$.[35]

To compare the volatility curve for the two models, we ensure that each moneyness category has sufficiently many options every day. Thus, if there are $N_{m,t}$ options in the moneyness category m that are quoted on day t, we include these options in our calculations if either $N_{m,t} \geq 6$ when m is the first category (all calls), or $N_{m,t} \geq 2$ for all the other categories (calls of a particular moneyness). Otherwise, the data corresponding to these options on day t is considered missing.[36]

To understand how the relative pricing errors are computed in Table 8, consider, e.g., the third moneyness category (ITM calls). Based on the number of observations reported in the table, there are only 58 target stocks for which there is at least one day with two or more quoted ITM calls. Then, for a target stock j and for a call option on j with (bid-ask mid-quote) price $C(t)$ quoted on day t on a stock with (closing) price $B(t)$ and with strike K, we compute the percentage pricing error by $\left|\big(C_M(t) - C(t)\big)/C(t)\right|$,

[35] The moneyness intervals follow Bakshi, Cao, and Chen (1997), except that their step (0.03) is smaller than our step (0.05), as the S&P 500 index options in their sample are much more liquid than the individual stock options in our sample.

[36] Imposing the condition $N_m \geq 2$ in Table 8, e.g., for ITM calls, reduces to 58 (out of 812) the number of firms for which there is at least one day t with two or more quoted ITM calls. The higher daily threshold $N \geq 6$ for all calls is chosen so that there are enough firms (374) satisfying this restriction. The results in Table 8 do not change qualitatively if we choose different thresholds for any particular category, as long as there are sufficiently many options in that category.

where $C_M(t)$ is the model-implied option price (BMR or BS). Let e_j be the average error over the ITM moneyness category on stock j. The table then shows various statistics of e_j over the cross section of 58 target stocks with non-missing ITM option data.

Overall, our model does significantly better than the BS model for the whole sample, as well as for the various subsamples of options. The average pricing error for all call options is 9.39% for the BMR model, and 19.49% for the BS model. The average pricing error for ITM call options is 6.97% for the BMR model, and 9.26% for the BS model. The average pricing error for ITM call options is 66.90% for the BMR model, and 84.17% for the BS model.

In Table 9, we compare the pricing errors in our model with the observed bid-ask spread. As the bid-ask spread is a measure of uncertainty regarding the price of a financial security, errors that are smaller than the bid-ask spread can be considered "small."

TABLE 9 ABOUT HERE

Table 9 shows summary statistics for the ratio of the absolute pricing error of a call option, relative to the observed bid-ask spread, i.e., $\left|\left(C_{\text{BMR}}(t) - C(t)\right)/s(t)\right|$, where $C_{\text{BMR}}(t)$ is the model-implied option price, $C(t)$ is the call option bid-ask mid-quote, and $s(t)$ is its quoted bid-ask spread. According to Table 9, the 75th percentile of this relative pricing error is less than 1 for all moneyness categories. Moreover, we compute that the 97% percentile of the relative pricing error for all call options is 0.85. Thus, for at least 97% of all options in our sample, the pricing errors are within the bid-ask spread. In this sense, our model performs fairly well.

Table 10 shows a comparison of percentage errors in put option prices according to the two models (BMR and BS). Note that our model works in principle only for European call options that expire after the effective date (see Proposition 1). By contrast, it may be optimal to exercise an American put option before expiration. Nevertheless, we can estimate the put option price using the same approximate equations as in (17) and (18). Compared to Table 8, which shows that our model does significantly better than the BS model for call options, Table 10 shows that our model works only slightly better than the BS model for put options.

TABLE 10 ABOUT HERE

5 Discussion and Robustness

In this section, we consider several alternative assumptions for the observed and latent variables. Several extensions of our option pricing formulas are left to the Appendix: In Appendix B, we analyze the pricing of options on the target company which expire before the effective day of the merger. In Appendix C, we analyze the case when the success probability and fallback price are correlated.

5.1 Assumptions on Observed Variables

In the baseline model in Section 2.1, we assume that the effective date T_e is known from the beginning. As a consequence, in our empirical tests we have taken T_e to be the date when the merger is either successful or fails. However, in reality the effective date of the merger subsequently changes from the initial date reported on the merger announcement day (see Table 1 for some statistics regarding the number of effective date changes). We address this concern in several ways. First, in contrast with our baseline specification in which only options with the shortest expiration date after T_e are considered, we also include call options with longer maturity. When we do so, our main results do not change qualitatively. Second, in Appendix B, we show theoretically that considering options with expiration date before T_e produces in general relatively small errors.

In our empirical methodology, we assume that when the cash offer price B_1 changes, in the formulas it gets simply replaced with the new value. That is, if we denote by $\tilde{B}_1(t)$ the time series of the offer price, as in equation (7) we write the stock price as $B(t) = q(t)\tilde{B}_1(t)\,\mathrm{e}^{-r(T_e-t)} + (1-q(t))B_2(t)$. Alternatively, if that the market knows that B_1 is stochastic (but independent from the other processes), Proposition 1 implies that $B(t) = q(t)B_1(t) + (1-q(t))B_2(t)$, where $B_1(t)$ is the market price at t of a contingent security that pays the (random) offer price on the effective date T_e. Thus, as long as $B_1(t)$ stays close to the discounted value of the current offer price, $\mathrm{e}^{-r(T_e-t)}\,\tilde{B}_1(t)$, the error is small. This assumption is plausible if the volatility of $\tilde{B}_1$ is small. Table 1 shows that this is a plausible assumption, as the offer price changes only rarely and usually not by large amounts.[37]

Other observed variables are the target stock price $B(t)$, and the call option price $C(t)$. In an alternative specification, instead of the usual bid-ask mid-quote, we use the ask price. This does not change our results qualitatively. The option pricing errors in Table 8 corresponding to our model become somewhat larger, although still significantly smaller than the errors corresponding to the BS model.

5.2 Assumptions on Latent Variables

In our baseline methodology, the success probability $q(t)$ is assumed to follow a process of the form $\mathrm{d}q(t)/\big(q(t)(1-q(t))\big) = \mu_1 \mathrm{d}t + \sigma_1 \mathrm{d}W_1(t)$ (see equation (15)). We have tested our estimation procedure under many alternative specifications for $q(t)$, including defining $q(t)$ as the price of a digital option on a diffusion process $X_1(t)$ with increments $\mathrm{d}X_1(t) = \mu_1 \mathrm{d}t + \sigma_1 \mathrm{d}W_1(t)$, or defining $q(t)$ as the transformation of the same process $X_1(t)$ via the logistic function $L(x) = \mathrm{e}^x / (1 + \mathrm{e}^x)$. Our results do not change significantly under the alternative specifications for q, although in some cases, e.g., the logistic specification, the algorithm converges much less often and thus fewer estimates are obtained.[38]

We consider the possibility that the success probability and the fallback price are correlated. To address this issue, we consider the specifications for $q(t)$ and $B_2(t)$ as in equations (15) and (16), except that the corresponding Itô increments $\mathrm{d}W_1$ and $\mathrm{d}W_2$ are no longer independent, but instead have a bivariate normal distribution, with instantaneous correlation $\rho \in [-1, 1]$. In Appendix C, we show that the formulas for stock and option prices are more complicated and involve numerical integration, which slows our estimation procedure by a factor of at least 100. Moreover, when we perform the estimation for the 10 companies in Table 3, in all cases the parameter ρ is poorly

[37] In an unreported extension to Table 1, the offer price changes at least once for only 80 deals (out of 812), and in those cases the average relative change is about 5%. In principle, we can modify our model in order to estimate the volatility of B_1, but the offer price does not change frequently enough to allow proper statistical identification.

[38] The logistic function $L(x)$ is nearly constant when x is large. Thus, when the process X_1 randomly drifts towards large values, the estimated posterior density is essentially flat and cannot distinguish between different values, which allows the process X_1 to further diverge.

identified, i.e., its estimated posterior likelihood is essentially flat. We interpret this result as suggesting that *a priori* it is not clear what sign the correlation ρ should have. Indeed, small changes in B_2 are not likely to affect q, while larger changes in B_2 in either direction may actually decrease q, thus pointing to a potentially non-linear relationship between q and B_2.

There is one method by which we can avoid specifying q altogether: As stock price errors are relatively small (see Table 7), we can assume that equation (17) holds without error, i.e., $\varepsilon_B(t) = 0$. In that case, the success probability $q(t)$ can be expressed as a function of the fallback price $B_2(t)$ and substituted in equation (18). To simplify formulas, denote by $B_1(t) = B_1 \, \mathrm{e}^{-r(T_e - t)}$, $C_1(t) = (B_1 - K)_+ \, \mathrm{e}^{-r(T_e - t)}$, and $C_2(t) = C_{\mathrm{BS}}(B_2(t), K, r, T - t, \sigma_2)$, where C_{BS} satisfies the BS formula (9). Equations (17) and (18) imply:

$$q(t) = \frac{B(t) - B_2(t)}{B_1(t) - B_2(t)}, \quad C(t) = C_2(t) + \frac{B(t) - B_2(t)}{B_1(t) - B_2(t)} \big(C_1(t) - C_2(t) \big) + \eta_C(t). \quad (22)$$

Thus, the fallback price becomes the only latent variable and we avoid specifying a functional form for $q(t)$. However, the constraint $q(t) \in [0, 1]$ must be imposed, i.e., $B_2(t)$ must be such that $\big(B(t) - B_2(t)\big) / \big(B_1(t) - B_2(t)\big) \in [0, 1]$. Thus, when $B_2(t)$ is close to the discounted offer price $B_1(t)$, the estimation is likely to generate large errors, hence it is not surprising that the estimates using this method are much noisier than those obtained under our baseline specification. Qualitatively, however, our results do not change under this alternative method.

Overall, our main results appear to be robust under various alternative specifications of the baseline model. One explanation for this robustness is that only a simple model can address the large amount of noise present in option prices on individual companies. Table 2 shows that the average percentage bid-ask spread of call options written on the target companies in our cash merger sample is 27.46%. Thus, attempts to impose additional structure on our baseline model typically result in increasing the noise in our estimates, whle not significantly changing our main results.

6 Conclusion

We have studied both theoretically and empirically option prices on target firms undergoing a cash merger offer. Using a state space representation of our model, we estimate the unobserved success probability of the merger and the target company's fallback price. Our success probability measure has significant predictive power for the merger outcome, even after controlling for variables used in the merger literature, including the "naive" probability.

As predicted by our model, we find that the target firms of cash mergers should display a pronounced pattern in their implied volatility curve during the life of the deal. This volatility smile is more pronounced when the merger is more likely to being successful. Theoretically, call options on the target of a cash merger should have a kink when the strike price is equal to the merger offer price, or equivalently there should be a kink in the target's implied volatility curve. The magnitude of the call price kink (the slope difference) should be equal to the merger's success probability, discounted at the risk-free rate. Empirically, we find strong support for these predictions.

The average merger risk premium in our sample is about 122% annually, which is consistent with the cash mergers literature, although there is evidence the premium has decreased substantially in the later period.

Our estimation method is flexible and can incorporate other existing information such as prior beliefs about the variables and the parameters of the model. It can also be used to compute option pricing for "stock-for-stock" mergers or "mixed-stock-and-cash" mergers, where the offer is made using the acquirer's stock or a combination of stock and cash. In principle, one could use our method to estimate the synergies of the deal. We leave such extensions for future research.

Appendix A. Proofs of Results

Proof of Proposition 1. Recall that T_e' is the instant after T_e when the merger uncertainty is resolved, and Q' is the extension of the equivalent martingale measure Q to $[0, T_e] \cup \{T_e'\}$. As $q(T_e')$ is either 1 or 0 depending on whether the merger is successful or not, the target's payoff at T'_e is

$$B(T_e) \;=\; q(T'_e)B_1(T'_e) + (1 - q(T'_e))B_2(T'_e), \tag{A1}$$

We apply Theorem 6J in Duffie (2001) for redundant securities. Markets are dynamically complete before T_e, because the uncertainty stems from the three Brownian motions involved in the definition of the securities B_1, B_2, and p_m. Moreover, at T_e, the stock price has a binary uncertainty that can be spanned only by the bond and p_m. Then, in the absence of arbitrage, any other security whose payoff depends on B_1, B_2, p_m is a discounted Q'-martingale. In particular, the price of the target company $B(t)$ is a discounted Q'-martingale, that is,

$$\begin{aligned} B(t) \;&=\; \mathrm{e}^{-r(T_e-t)}\ \mathsf{E}_t^{Q'}\Big(q(T'_e)B_1(T'_e) + (1 - q(T'_e))B_2(T'_e)\Big) \\ &=\; \mathsf{E}_t^{Q'}\big(q(T'_e)\big)\,\mathrm{e}^{-r(T_e-t)}\,\mathsf{E}_t^{Q'}\big(B_1(T'_e)\big) + \mathsf{E}_t^{Q'}\big(1 - q(T'_e)\big)\,\mathrm{e}^{-r(T_e-t)}\,\mathsf{E}_t^{Q'}\big(B_2(T'_e)\big) \\ &=\; q(t)B_1(t) + \big(1 - q(t)\big)B_2(t), \end{aligned} \tag{A2}$$

where for the second equation we use the independence of B_1, B_2 and q. This proves equation (4).

Consider a European call option on B with strike K and maturity $T \geq T_e$. Denote by $C^{K,T}(t)$ its price at $t \leq T_e$, and by $X_+ \;=\; \max\{X, 0\}$. Denote by $C_i^{K,T}(t)$ the price of a European call option on B_i with strike K and maturity T. Consider the payoff of the call at $t = T \geq T'_e$:

$$q(T'_e)\big(B_1(T'_e) - K\big)_+\,\mathrm{e}^{T-T_e} + (1 - q(T'_e))\big(B_2(T) - K\big)_+. \tag{A3}$$

where by assumption all cash obtained after the effective date T_e is invested at the risk-free rate r. By a similar calculation as above, the call price at t is

$$\begin{aligned} C^{K,T}(t) \;&=\; \mathrm{e}^{-r(T-t)}\ \mathsf{E}_t^{Q'}\Big(q(T'_e)\big(B_1(T'_e) - K\big)_+\,\mathrm{e}^{r(T-T_e)} + (1 - q(T'_e))\big(B_2(T) - K\big)_+\Big) \\ &=\; q(t)C_1^{K,T_e}(t) + \big(1 - q(t)\big)C_2^{K,T}(t), \end{aligned} \tag{A4}$$

which proves equation (5).

Next, we show that it is not optimal to exercise early an American option on B with strike K and expiration T. For this, it is sufficient to prove that the European call option price, $C^{K,T}(t)$, is always larger than the exercise value, $B(t) - K$. Equations (4) and (5) imply that:

$$C^{K,T}(t)-\big(B(t)-K\big) \;=\; q(t)\Big(C_1^{K,T_e}(t)-\big(B_1(t)-K\big)\Big)+(1-q(t))\Big(C_2^{K,T}(t)-\big(B_2(t)-K\big)\Big). \tag{A5}$$

By assumption, $C_i^{K,T_e}(t) - \big(B_i(t) - K\big) > 0$, $i = 1, 2$, hence $C^{K,T}(t) - \big(B(t) - K\big) > 0$, which finishes the proof. □

Proof of Corollary 1. Equation (8) implies that the call price satisfies $C^{K,T}(t) = q(t)\,\mathrm{e}^{-r(T_e-t)}(B_1 - K)_+ + (1 - q(t))C_2^{K,T}(t)$, where $C_2^{K,T}(t)$ satisfies the BS equation (9). Thus, its partial derivative with respect to K is:

$$\frac{\partial C_2^{K,T}(t)}{\partial K} \;=\; -\,\mathrm{e}^{-r(T-t)}\,\Phi(d_-), \tag{A6}$$

which is continuous in K. We differentiate $C^{K,T}(t)$ with respect to K to the left and to the right of $K = B_1$:

$$\begin{aligned} \left(\frac{\partial C}{\partial K}\right)_{K\uparrow B_1} &= -q(t)\,\mathrm{e}^{-r(T_e-t)} - \big(1 - q(t)\big)\frac{\partial C_2^{K,T}(t)}{\partial K}, \\ \left(\frac{\partial C}{\partial K}\right)_{K\downarrow B_1} &= -\big(1 - q(t)\big)\frac{\partial C_2^{K,T}(t)}{\partial K}. \end{aligned} \tag{A7}$$

The kink is the difference:

$$\left(\frac{\partial C}{\partial K}\right)_{K\downarrow B_1} - \left(\frac{\partial C}{\partial K}\right)_{K\uparrow B_1} = q(t)\,\mathrm{e}^{-r(T_e-t)}, \tag{A8}$$

which proves equation (10).

Let $\tau_e = T_e - t$ and $\tau = T - t$. By definition, the BS-implied volatility σ_{impl} of $C^{K,T}(t)$ satisfies $C^{K,T}(t) = C_{\text{BS}}(B(t), K, r, \tau, \sigma_{\text{impl}})$, where C_{BS} satisfies the BS formula (9). By differentiating $C(t) = C_{\text{BS}}(B(t), K, r, \tau, \sigma_{\text{impl}})$ with respect to K, we get:

$$\left(\frac{\partial \sigma_{\text{impl}}}{\partial K}\right)_{K \downarrow B_1} = \frac{\left(\frac{\partial C}{\partial K}\right)_{K\downarrow B_1} + \mathrm{e}^{-r\tau}\,\Phi\big(d_-(B(t), K, r, \tau, \sigma_{\text{impl}})\big)}{\nu\big(B(t), K, r, \tau, \sigma_{\text{impl}}\big)}, \tag{A9}$$

and a similar formula for $\left(\frac{\partial \sigma_{\text{impl}}}{\partial K}\right)_{K\uparrow B_1}$. Taking the difference of these two formulas, we obtain equation (11).

Next, set $q(t) = 1$ and $T_e = T$. Then $\tau_e = \tau$, and

$$\begin{aligned} \left(\frac{\partial \sigma_{\text{impl}}}{\partial K}\right)_{K \downarrow B_1} &= \frac{\mathrm{e}^{-r\tau}}{\nu(B, K, r, \tau, \sigma_{\text{impl}})}\Big(-1 + \Phi\big(d_-(B, K, r, \tau, \sigma_{\text{impl}})\big)\Big) \;<\; 0, \\ \left(\frac{\partial \sigma_{\text{impl}}}{\partial K}\right)_{K \uparrow B_1} &= \frac{\mathrm{e}^{-r\tau}}{\nu(B, K, r, \tau, \sigma_{\text{impl}})}\Big(\Phi\big(d_-(B, K, r, \tau, \sigma_{\text{impl}})\big)\Big) \;>\; 0. \end{aligned} \tag{A10}$$

By continuity, the two inequalities above also hold when $q(t)$ is sufficiently close to 1 and T_e is sufficiently close to T. This finishes the proof. □

Proof of Corollary 2. To obtain equation (14), one applies standard Itô calculus to differentiate equation (7). To prove the result regarding the implied volatility, let $T_e = T$. In what follows, we denote $X \approx Y$ to mean $\lim_{q(t)\to 0}(X - Y) = 0$. When the volatility is 0, the BS formula implies $C_{\text{BS}}\big(S, K, r, \tau, 0\big) = (S - K\,\mathrm{e}^{-r\tau})_+$. When $q(t) \approx 1$, equations (7) and (8) imply that $B(t) \approx B_1\,\mathrm{e}^{-r\tau}$ and $C^{K,T}(t) \approx (B_1 - K)_+\,\mathrm{e}^{-r\tau}$. Thus, we obtain $C^{K,T}(t) \approx C_{\text{BS}}\big(B(t), K, r, \tau, 0\big)$. By definition, $C^{K,T}(t) = C_{\text{BS}}\big(B(t), K, r, \tau, \sigma_{\text{impl}}\big)$, hence $\sigma_{\text{impl}} \approx 0$. This finishes the proof. □

Appendix B. Expiration Before Effective Date

We consider the same setup as in Section 2.1 in the paper, except that that we consider options that expire before the effective date. To simplify the presentation, we assume that the offer price B_1 is constant, the fallback price $B_2(t)$ is a log-normal process with constant coefficients, and the bet price $p_m(t)$ is the price of a digital option that pays 1 if $B_3(T_e)$ is above K_3 and 0 otherwise, where $B_3(t)$ is a log-normal process with constant coefficients. Therefore, the increments of $B_2(t)$ and $B_3(t)$ satisfy:

$$\mathrm{d}B_i(t) \;=\; \mu_i B_i(t)\mathrm{d}t + \sigma_i B_i(t)\mathrm{d}W_i(t), \quad i \;=\; 2,3. \tag{B1}$$

For any $T \geq t$, we use the risk-neutral BS formalism to compute:

$$B_i(T) \;=\; B_i(t)\exp\Big(\big(r - \tfrac{\sigma_i^2}{2}\big)(T-t) + \sigma_i\sqrt{T-t}\,\varepsilon_i\Big), \quad i \;=\; 2,3, \tag{B2}$$

where ε_2 and ε_3 have independent standard normal distributions. Similarly, for any $T \in (t, T_e)$, the risk-neutral probability q satisfies:

$$q(T) \;=\; \Phi\left(\frac{\sqrt{T_e - t}\,\Phi^{-1}\big(q(t)\big) + \sqrt{T-t}\,\varepsilon_3}{\sqrt{T_e - T}}\right), \tag{B3}$$

where ε_3 has a standard normal distribution.

In Proposition 2, we provide (without proof) the price of a European call that expires before T_e.[39]

Proposition 2. *Suppose B_2 and q are processes with independent increments, and B_1 is constant. For each $T < T_e$, define the process:*

$$B_1(T) \;=\; B_1\,\mathrm{e}^{-(T_e - T)}, \quad \bar{\varepsilon} \;=\; \begin{cases} \frac{\sqrt{T_e - T}}{\sqrt{T-t}}\,\Phi^{-1}\left(\frac{K}{B_1(T)}\right) - \frac{\sqrt{T_e - t}}{\sqrt{T-t}}\,\Phi^{-1}\big(q(t)\big), & \text{if } K < B_1(T), \\ +\infty, & \text{if } K \geq B_1(T) \end{cases} \tag{B4}$$

The price at t of a European call option on B with strike K and expiration $T < T_e$ is:

$$\begin{aligned} C(t) \;=\; & \int_{-\infty}^{\bar{\varepsilon}} \cdot\Big[\big(q(T)B_1(T) - K\big)\,\mathrm{e}^{-r(T-t)} \;+\; \big(1 - q(T)\big)\,B_2(t)\Big]\phi(\varepsilon_3)\,\mathrm{d}\varepsilon_3 \\ & + \int_{\bar{\varepsilon}}^{+\infty} \Big[\big(q(T)B_1(T) - K\big)\,\mathrm{e}^{-r(T-t)}\;\Phi\Big(d_-\big(B_2(t), \tfrac{K - q(T)B_1(T)}{1 - q(T)}, T-t\big)\Big) \\ & \qquad + \big(1 - q(T)\big)\,B_2(t)\,\Phi\Big(d_+\big(B_2(t), \tfrac{K - q(T)B_1(T)}{1 - q(T)}, T-t\big)\Big)\Big]\,\phi(\varepsilon_3)\,\mathrm{d}\varepsilon_3, \end{aligned} \tag{B5}$$

where $q(T)$ is the function of ε_3 in equation (B3) and $d_\pm(S, K, T-t)$ is as in equation (9) with arguments r and σ_2 omitted.

[39] The proof follows the standard risk-neutral BS formalism and is available from the authors upon request.

FIGURE 5 ABOUT HERE

In Figure 5, we compare the correct price in equation (B5) to the "simple" price from equation (8), which is correct only if $T > T_e$. The goal is to examine whether a stochastic effective date significantly affects the option price. Suppose at $t = 0$ the current effective date of the merger is in $T_e = 80$ days, and we consider a European call option with strike $K = 95$ and expiration in $T = 90$ days.[40] According to equation (8), the call price is $C_{\text{simple}} = 6.0408$. If the effective date suddenly changes to $T_e = 100$, the option expires before T_e, and equation (B5) implies that $C_{\text{correct}} = 5.4906$. If instead we use equation (8), which is no longer correct, we have $C_{\text{simple}} = 6.0360$, which is slightly smaller than before (by 0.08%) as the cash offer is now expected later. The corresponding pricing error is $(C_{\text{simple}} - C_{\text{correct}})/C_{\text{correct}} = 9.9336\%$, which in Figure 5 corresponds to the point on the curve $K = 95$ with x-coordinate $T = 90$. This error, however, assumes that the effective date changes with certainty at $t = 0$. If the probability of an effective date change is smaller, e.g., 1% per day, then the actual pricing error is much smaller than 9.9336%.[41]

Appendix C. Correlated Latent Variables

We consider the same setup as in Section 2.1 in the paper, except that the success probability and the fallback price are correlated. We make the same assumptions as in Appendix B, with the same specifications as in equations (B1) and (B2), except that ε_2 and ε_3 are no longer independent but have a bivariate normal distribution with density:

$$f_\rho(x, y) \;=\; \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left(-\frac{x^2 + y^2 - 2\rho xy}{2(1-\rho^2)}\right). \tag{C1}$$

In Proposition 3, we extend the formulas (7) and (8) to the case when q and B_2 are correlated.

[40]The parameters values are $B_1 = 100$, $B_2(0) = 90$, $q(0) = 0.5$, and $r = 0.0.5$. To annualize the number of days, we divide by 252, which by convention is the number of trading days in one year.

[41]Table 1 shows that the effective date changes on average 0.74 times for a deal duration which on average is 66.6 trading days, hence the probability of an effective date change during any particular day is $0.74/66.6 \approx 1.11\%$.

Proposition 3. *If B_1 is constant, and B_2 and q are correlated processes as above, then the target's stock price satisfies for $t < T_e$*

$$B(t) \;=\; q(t)B_1\,\mathrm{e}^{-r(T_e-t)} \;+\; \Big(1-\Phi\Big(\Phi^{-1}\big(q(t)\big)+\rho\sigma_2\sqrt{T-t}\Big)\Big)\;B_2(t). \tag{C2}$$

The price of a European call option on B with strike K and expiration $T \geq T_e$ is

$$C^{K,T}(t) \;=\; q(t)(B_1-K)_+\,\mathrm{e}^{-r(T_e-t)} \;+C_{\mathrm{BS}}\big(B_2(t),T-t\big) \tag{C3}$$

$$-\int_{-\infty}^{+\infty}\Phi\left(\frac{\Phi^{-1}(q(t))+\rho\varepsilon_2}{\sqrt{1-\rho^2}}\right)\,C_{\mathrm{BS}}\left(B_2(t)\exp\Big(\big(r-\tfrac{\sigma_2^2}{2}\big)(T_e-t)+\sigma_2\sqrt{T_e-t}\,\varepsilon_2\Big),T-T_e\right)\,\phi(\varepsilon_2)\,\mathrm{d}\varepsilon_2,$$

where $C_{\mathrm{BS}}(S,T-t)$ is the BS formula (9) with arguments K, r and σ_2 omitted.

Proof of Proposition 3. The non-trivial part of proving equation (C2) is the computation of the term:

$$\mathsf{E}_t^Q\big(q(T_e)B_2(T_e)\big) \;=\; \mathsf{E}_t^Q\big(\mathbf{1}_{B_3(T_e)\geq K_3}B_2(T_e)\big), \tag{C4}$$

where $\mathbf{1}_{B_3(T_e)\geq K_3}$ is the indicator function, which is 1 if $B_3(T_e)\geq K_3$ or 0 otherwise. From equation (B2), we get $\ln\big(B_3(T_e)/K_3\big)=\ln\big(B_3(t)/K_3\big)+\big(r-\sigma_3^2/2\big)(T_e-t)+\sigma_3\sqrt{T_e-t}\varepsilon_3$, which implies that $B_3(T_e)\geq K_3$ is equivalent to $\varepsilon_3\geq -\Phi^{-1}(q(t))$. From equation (B2), we write $B_2(T_e)=a_2\,\mathrm{e}^{b_2\varepsilon_2}$ for $a_2=B_2(t)\exp\big((r-\sigma_2^2/2)(T_e-t)\big)$ and $b_2=\sigma_2\sqrt{T_e-t}$. As ε_2 and ε_3 are bivariate normal with correlation ρ, if we define $\bar{\varepsilon}_3=-\Phi^{-1}(q(t))$, we have:

$$\begin{aligned}\mathsf{E}_t^Q\big(\mathbf{1}_{B_3(T_e)\geq K_3}B_2(T_e)\big) \;&=\; a_2\int_{\bar{\varepsilon}_3}^{+\infty}\int_{-\infty}^{+\infty}\mathrm{e}^{b_2\varepsilon_2}\,f_\rho(\varepsilon_2,\varepsilon_3)\,\mathrm{d}\varepsilon_2\,\mathrm{d}\varepsilon_3\\ &=\; a_2\int_{\bar{\varepsilon}_3}^{+\infty}\mathrm{e}^{b_2^2/2}\,\phi(\varepsilon_3-\rho b_2)\,\mathrm{d}\varepsilon_3 \;=\; a_2\,\mathrm{e}^{b_2^2/2}\;\Phi(\rho b_2-\bar{\varepsilon}_3).\end{aligned} \tag{C5}$$

As $a_2\,\mathrm{e}^{b_2^2/2}=B_2(t)\,\mathrm{e}^{r(T_e-t)}$ and $-\bar{\varepsilon}_3=\Phi^{-1}(q(t))$, we obtain

$$\mathsf{E}_t^Q\big(q(T_e)B_2(T_e)\big) \;=\; B_2(t)\,\mathrm{e}^{r(T_e-t)}\,\Phi\big(\Phi^{-1}(q(t))+\rho\sigma_2\sqrt{T-t}\big). \tag{C6}$$

The proof for the rest of equation (C2) is straightforward.

The non-trivial part of proving equation (C3) is the computation of the term:

$$\begin{aligned}\mathsf{E}_t^Q\Big[\mathrm{e}^{-r(T-t)}\, q(T)\big(B_2(T)-K\big)_+\Big] &= \mathsf{E}_t^Q\Big[q(T_e)\ \mathrm{e}^{-r(T_e-t)}\ \mathsf{E}_{T_e}^Q\Big(\mathrm{e}^{-(T-T_e)}\big(B_2(T)-K\big)_+\Big)\Big] \\ &= \mathsf{E}_t^Q\Big[\mathbf{1}_{B_3(T_e)\geq K_3}\ \mathrm{e}^{-r(T_e-t)}\ C_{\mathrm{BS}}\big(B_2(T_e), T-T_e\big)\Big],\end{aligned} \tag{C7}$$

where $C_{\mathrm{BS}}(S, T-t)$ is the BS formula (9) with arguments K, r, and σ_2 omitted. We can no longer integrate along ε_2, as the function C_{BS} is not elementary. However, we integrate along ε_3, using the formula:

$$\int_{\bar{\varepsilon}_3}^{+\infty} f_\rho(\varepsilon_2, \varepsilon_3)\, \mathrm{d}\varepsilon_3 \;=\; \phi(\varepsilon_2)\Phi\left(\frac{\rho\varepsilon_2-\bar{\varepsilon}_3}{\sqrt{1-\rho^2}}\right). \tag{C8}$$

Substituting equation (C8) into equation (C7), we get the same integral as in equation (C3). The proof for the rest of equation (C3) is straightforward. □

Appendix D. MCMC Procedure for Cash Mergers

In this section we describe a Markov Chain Monte Carlo method based on the state space representation of our model. The goal is to use the time series of observed stock prices and prices of various call options on the target companies, and estimate the time series of the two latent variables: the success probability of the merger $q(t)$, and the fallback price of the target $B_2(t)$.

To simplify the presentation, we consider slightly different processes for q and B_2:[42]

$$q(t) \;=\; \frac{\mathrm{e}^{X_1(t)}}{1+\mathrm{e}^{X_1(t)}}, \quad B_2(t) \;=\; \mathrm{e}^{X_2(t)}, \quad \mathrm{d}X_i(t) \;=\; \mu_i \mathrm{d}t + \sigma_i \mathrm{d}W_i(t), \quad i=1,2, \tag{D1}$$

where $W_1(t)$ and $W_2(t)$ are independent standard Brownian motions. The observation

[42] Using Itô calculus, one can verify that the specifications of q and B_2 given in equation (D1) differ from the ones used in equations (15) and (16) only by a drift term.

equation combines equations (17) and (18):

$$\begin{aligned} B(t) &= q(t)B_1\,\mathrm{e}^{-r(T_e-t)} + (1-q(t))B_2(t) + \varepsilon_B(t), \\ C(t) &= q(t)(B_1-K)_+\,\mathrm{e}^{-r(T_e-t)} + (1-q(t))C_{\mathrm{BS}}(B_2(t),K,T-t) + \varepsilon_C(t), \end{aligned} \tag{D2}$$

where $C_{\mathrm{BS}}(S,K,T-t)$ is the BS formula (9) with arguments r and σ_2 omitted. The errors $\varepsilon_B(t)$ and $\varepsilon_C(t)$ are IID normal with zero mean, and independent from each other. If more than one call option is employed in the estimation process, $C(t)$ is multi-dimensional.

To simplify notation, we rename the observed variables: $Y_B = B$, and $Y_C = C$. The state variables are collected under $X = [X_1, X_2]^T$, and the observed variables are collected under $Y = [Y_B, Y_C]^T$. (The superscript T after a vector indicates transposition.) There are other observed parameters: the effective date (T_e), the interest rate (r), the cash offer (B_1), and the strike prices (K) and maturities (T) of various call options on the company B.

The vector of latent parameters is $\theta = [\mu_1, \mu_2, \sigma_1, \sigma_2]^T$. The observation equations (17) and (18) can be rewritten as $Y = f(X,\theta) + \varepsilon$, where $\varepsilon = [\varepsilon_B, \varepsilon_C]^T$ is the vector of model errors. The diagonal matrix of model error variances, $\Sigma_\varepsilon = \mathrm{diag}\big(\sigma^2_{\varepsilon_B}, \sigma^2_{\varepsilon_C}\big)$ is called the matrix of hyperparameters.

The MCMC method provides a way to sample from the posterior distribution with density $p(\theta, X, \Sigma_\varepsilon | Y)$, and estimate the parameters θ, the state variables X, and the hyperparameters Σ_ε. Bayes' Theorem says that the posterior density is proportional to the likelihood times the prior density:

$$p(X,\Sigma_\varepsilon,\theta|Y) \;\propto\; p(Y|X,\Sigma_\varepsilon,\theta)\cdot p(X,\Sigma_\varepsilon,\theta) \;=\; p(Y|X,\Sigma_\varepsilon,\theta)\cdot p(X|\theta)\cdot p(\Sigma_\varepsilon)\cdot p(\theta). \tag{D3}$$

On the right hand side, the first term in the product is the likelihood for the observation equation, the second term is the likelihood for the state equation, and the third and fourth terms are the prior densities of the hyperparameters Σ_ε and the parameters θ.

We obtain:

$$p(Y|X, \Sigma_\varepsilon, \theta) \;=\; \prod_{t=1}^{T_e} \phi\big(Y(t)|f(X(t),\theta),\Sigma_\varepsilon\big), \quad p(X|\theta) \;=\; p(X(1)|\theta)\cdot\prod_{t=2}^{T_e}\phi\big(Z(t)|\mu,\Sigma_X\big), \tag{D4}$$

where $Z_i(t) \;=\; X_i(t) - X_i(t-1)$, $\mu = [\mu_1, \mu_2]^T$, $\Sigma_X = \mathrm{diag}\big(\sigma_1^2, \sigma_2^2\big)$, and

$$\phi(x|\mu,\Sigma) \;=\; (2\pi)^{-n/2}|\Sigma|^{-1/2}\exp\left(-\tfrac{1}{2}(x-\mu)^\top\Sigma^{-1}(x-\mu)\right) \tag{D5}$$

is the n-dimensional multivariate normal density with mean μ and covariance matrix Σ.

We describe the MCMC algorithm.

Step 0. Initialize $\theta^{(1)}$, $X^{(1)}$, $\Sigma_\varepsilon^{(1)}$. Fix a number of iterations M. Then for each $i = 1, \ldots M-1$, follow Steps 1–3 below.

Step 1. Update $\Sigma_\varepsilon^{(i+1)}$ from $p(\Sigma_\varepsilon|\theta^{(i)}, X^{(i)}, Y)$. With a flat prior for Σ_ε, we have:

$$p\big(\Sigma_\varepsilon|\theta^{(i)}, X^{(i)}, Y\big) \;\propto\; \prod_{t=1}^{T_e}\phi\big(Y(t)|f(X(t),\theta),\Sigma_\varepsilon\big). \tag{D6}$$

This implies that $\big(\sigma_{\varepsilon,j}^{(i+1)}\big)^2$, $j = B, C$, is sampled from an inverted gamma-2 distribution, $IG_2(s,\nu)$, with parameters $s = \sum_{t=1}^{T_e}(Y_j(t) - f_j(X(t),\theta))^2$ and $\nu = T_e - 1$. The inverted gamma-2 distribution has log-density $\ln p_{IG_2}(x) \;=\; -(\nu+1)/2 \times \ln(x) - s/(2x)$. One could also use a conjugate prior for Σ_ε, which is also an inverted gamma-2 distribution.

Step 2. Update $X^{(i+1)}$ from $p(X|\theta^{(i)}, \Sigma_\varepsilon^{(i+1)}, Y)$. Denote by $\theta = \theta^{(i)}$ and $\Sigma_\varepsilon = \Sigma_\varepsilon^{(i+1)}$. Assuming flat priors for X, $p(X|\theta,\Sigma_\varepsilon,Y) \propto p(Y|\theta,\Sigma_\varepsilon,X)\cdot p(X|\theta)$. For $t = 2,\ldots,T_e-1$, we have:

$$\begin{aligned} p(X(t)|\theta,\Sigma_\varepsilon,Y) \;\propto\;& \phi\big(Y(t)|f(X(t),\theta),\Sigma_\varepsilon\big) \\ &\cdot\; \phi\big(X(t) - X^{(i+1)}(t-1)|\mu,\Sigma_X\big) \\ &\cdot\; \phi\big(X^{(i)}(t) - X(t)|\mu,\Sigma_X\big). \end{aligned} \tag{D7}$$

If $t = 1$, we replace the second term in the product with $p(X(1)|\theta)$, and if $t = T$, we drop the third term out of the product. As this is a non-standard density, we sample from this distribution by using the Metropolis–Hastings algorithm, which is described after Step 3.

Step 3. Update $\theta^{(i+1)}$ from $p(\theta|X^{(i+1)}, \Sigma_\varepsilon^{(i+1)}, Y)$. Denote by $X = X^{(i+1)}$ and $\Sigma_\varepsilon = \Sigma_\varepsilon^{(i+1)}$. Assuming a flat prior for θ, $p(\theta|X, \Sigma_\varepsilon, Y) \propto p(Y|\theta, \Sigma_\varepsilon, X) \cdot p(X|\theta)$. Then, assuming that $X(1)$ does not depend on θ, we have:

$$p(\theta|X, \Sigma_\varepsilon, Y) \propto \prod_{t=1}^{T_e} \phi\big(Y(t)|f(X(t), \theta), \Sigma_\varepsilon\big) \cdot \prod_{t=2}^{T_e} \phi\big(X(t) - X(t-1)|\mu, \Sigma_X\big). \tag{D8}$$

As $\theta = [\mu_1, \mu_2 \sigma_1, \sigma_2]^T$, for the parameters μ_1, μ_2, and σ_1, we can drop the first product from the formula, since it does not contain these parameters. We make the following updates: $\mu_k^{(i+1)} \sim \Phi\Big(1/(T_e-1) \times \sum_{t=2}^{T_e}(X_k(t) - X_k(t-1))^2 \, , \, \big(\sigma_k^{(i)}\big)^2/(T_e-1)\Big)$, $k = 1, 2$, and $\big(\sigma_1^{(i+1)}\big)^2 \sim IG_2\Big(\sum_{t=2}^{T_e}\big(X_1(t) - X_1(t-1) - \mu_1^{(i+1)}\big)^2 \, , \, T_e - 2\Big)$. As the density is non-standard for the other parameters, we sample from the distribution by using the Metropolis–Hastings algorithm.

Metropolis–Hastings. This algorithm shows how to randomly extract a variable X from a distribution with given density $p(x)$: Start with a variable X_0 (e.g., in the MCMC algorithm, X_0 is the value of a parameter $\theta^{(i)}$, while X is the updated value $\theta^{(i+1)}$). Choose a conditional density $q(x|x_0)$, from which we know how to sample randomly. Let $X_{CURR} = X_0$ (this is the "current" X). The algorithm consists of the following steps:

1. Draw $X_{PROP} \sim q(x|X_{CURR})$ (this is the "proposed" X).
2. Compute $\alpha = \min\Big(\frac{p(X_{PROP})}{p(X_{CURR})} \times \frac{q(X_{CURR}|X_{PROP})}{q(X_{PROP}|X_{CURR})} \, , \, 1\Big)$.
3. Draw $u \sim U[0, 1]$, the uniform distribution on $[0, 1]$. If $u < \alpha$, set $X = X_{PROP}$ ("accept"), otherwise if $u \geq \alpha$, set $X = X_{CURR}$ ("reject").

Typically, we use the "Random-Walk" Metropolis–Hastings version, for which we choose the normal density $q(x|x_0) = \phi(x - x_0|0, a^2)$, $a > 0$. Equivalently, $X_{PROP} = X_{CURR} + e$, where $e \sim \mathcal{N}(0 \, , \, a^2)$.

In our empirical study, we choose the number of iterations to be $M = 400,000$ and we observe that the algorithm typically converges (i.e., the estimated posterior density appears stationary) after an initial "burn-out" period of about $200,000$ iterations. With these numbers, it takes our algorithm on average about one day per firm to finish at our current computing speed. Since we use the Metropolis–Hastings algorithm described above, we follow standard procedure and require that the average acceptance ratios are between 0.04 and 0.96; otherwise, we modify the value of the random walk parameter a until we obtain acceptance ratio in this interval. If this step fails as well (usually because there are very few options, with stale prices), the company is excluded from the sample.

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Figure 1: Average Implied Volatility Smile for Successful and Failed Mergers. This figure shows daily BS-implied volatilities for call options on the target company of the 843 cash mergers announced between January 1996 and December 2014 with options traded on the target company. In Graph A we select the (trading) dates 30 days to 1 day before the announcement date of the merger, while in Graph B we select the dates between the announcement date and the effective date of the merger. In both Graphs A and B we select the options with the earliest expiration date after the effective date of the merger. Option prices are either the bid price ("bid"), ask price ("ask"), or bid-ask mid-quote ("mid"). On the x-axis is the option moneyness m: if K is the strike price of the option and B_1 the cash offer price per share, for each $m \in \{0.7, 0.75, \ldots, 1.2\}$ we consider the average implied volatility corresponding to the call options for which K/B_1 rounds to m. We show two average implied volatilities: one computed only for the target companies in deals that eventually succeeded ("success") and one computed only for the target companies in deals that eventually failed ("failure").

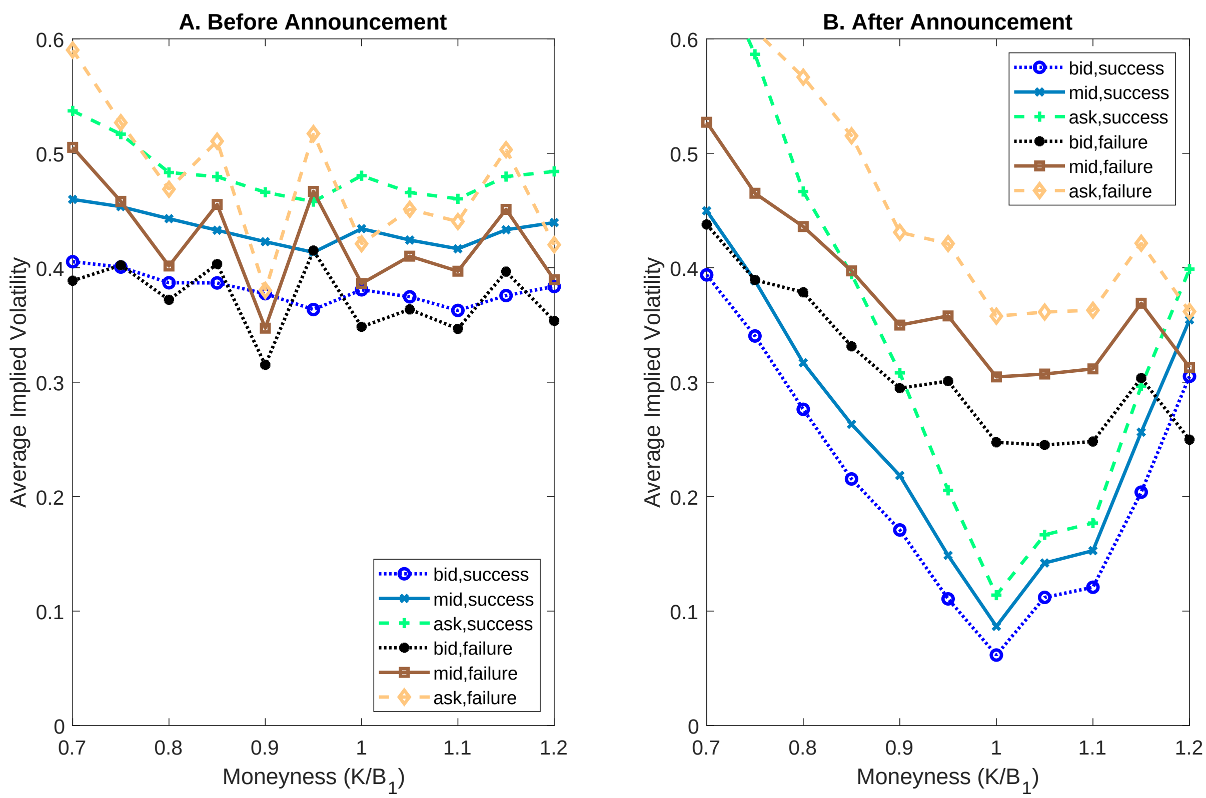

Figure 2: Time Series of Average Implied Volatilities. This figure shows the time series of average BS-implied volatilities for at-the-money call options on the target company of the 843 cash mergers announced between January 1996 and December 2014 with options traded on the target company. At each trading date 20 days before the announcement date (marked with "0") and the effective date of the merger (marked with "T_e"), we select the options with the earliest expiration date after the effective date. Option and underlying prices are the average between quoted ask and bid prices. We mark with "$*$" the average implied volatility for the deals that eventually succeeded, and with "$\circ$" the average implied volatility for the deals that eventually failed.

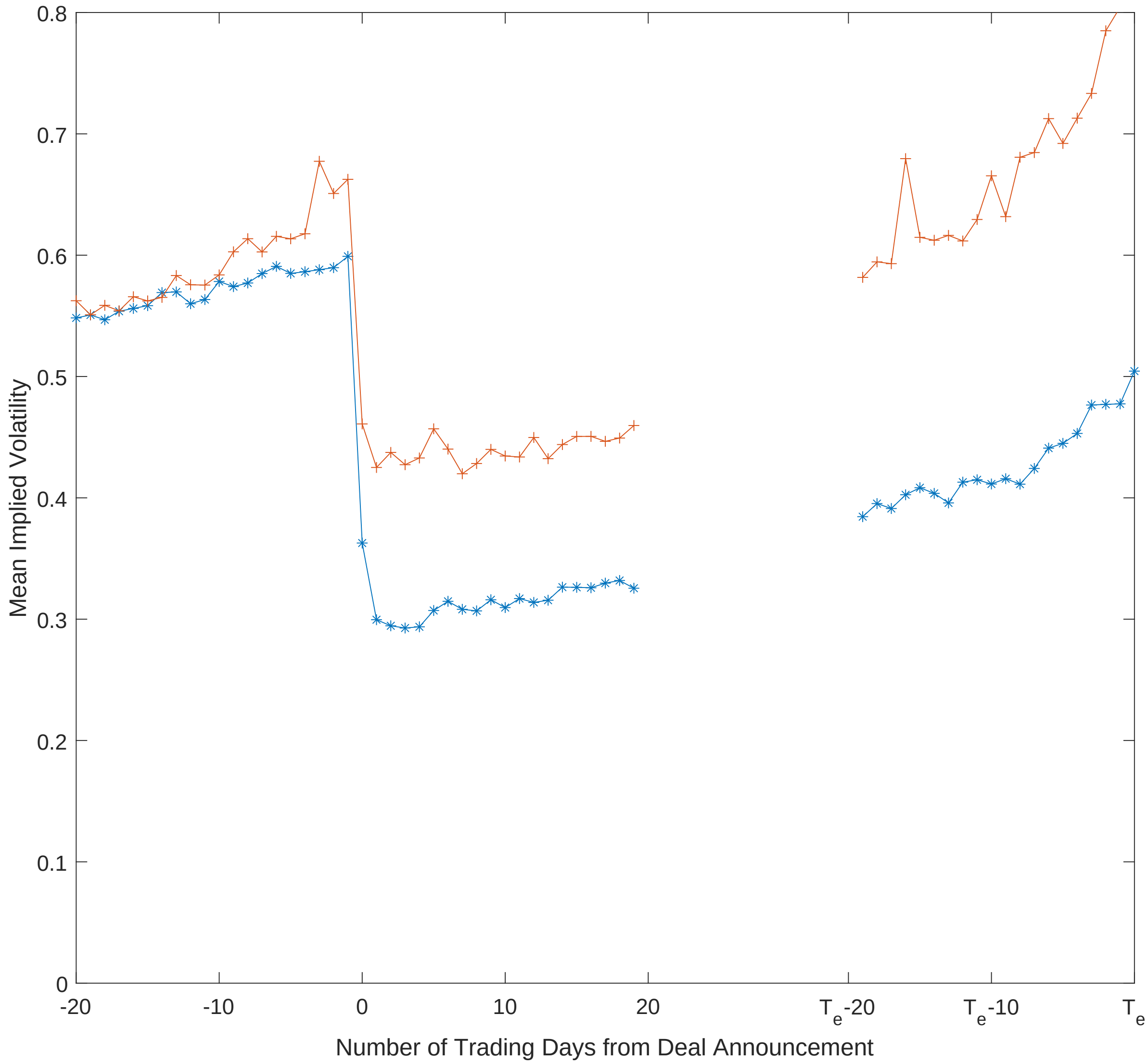

Figure 3: Success Probability Estimates for Ten Selected Cash Mergers. This figure shows the estimated success probability for the target companies in the subsample of 10 cash mergers in Table 3. The deals corresponding to target tickers BUD, AWE, TXU, AT, FDC succeeded, while those for SLM, MCIC, UCL, HET, AVP failed. The dash-dotted lines represent the 5% and 95% error bands around the estimated median values. The estimates are obtained using the call options on the target company with the earliest expiration date after the effective date of the merger.

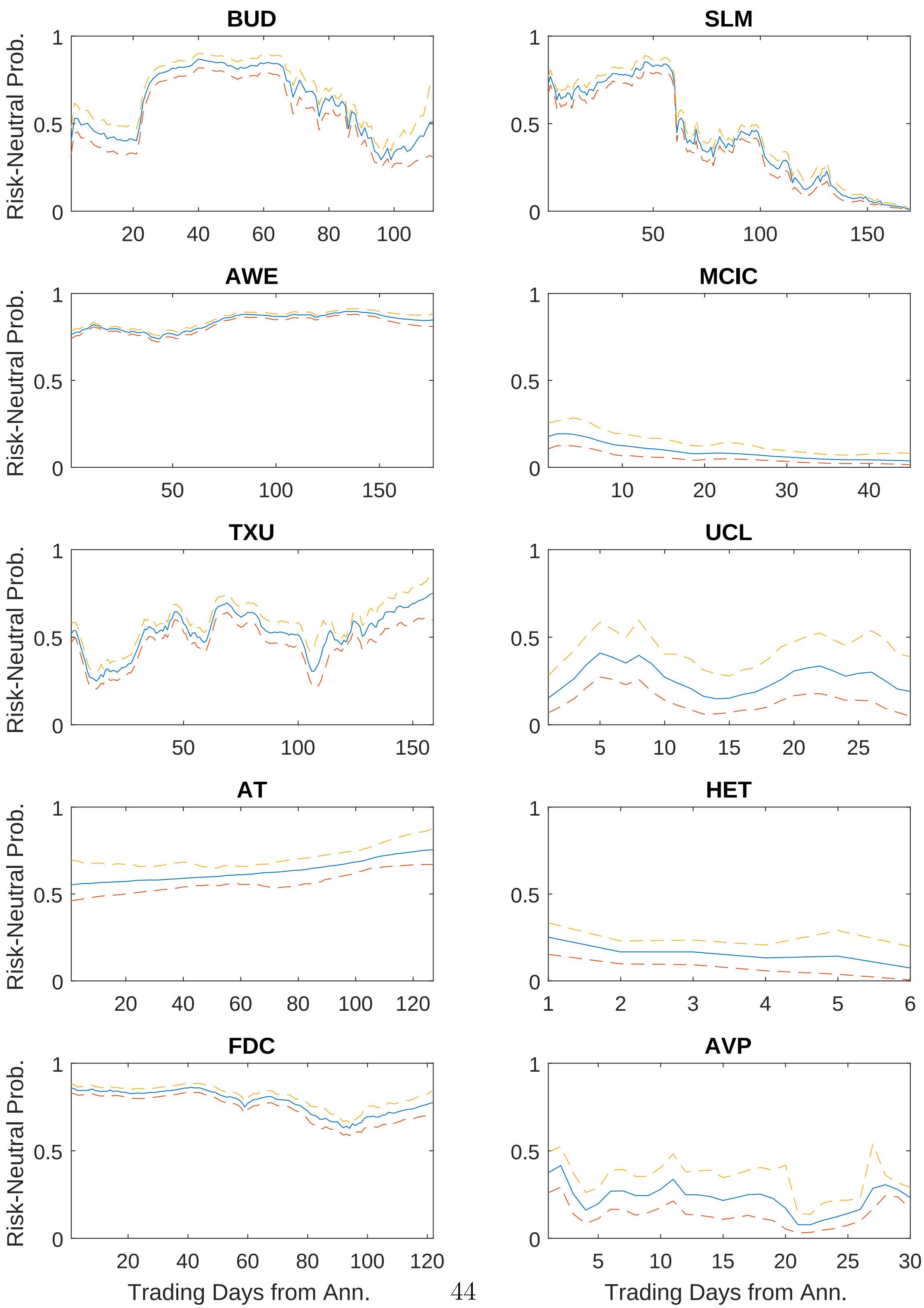

Figure 4: **Comparison of Observed and Theoretical Volatility Smiles for AWE.** From the sample of 10 large cash merger deals in Table 3 we select the deal with the largest offer premium (75.44%). The deal has target company AT&T Wireless, with ticker AWE. This figure shows the observed and theoretical volatility smiles of call options traded on AWE, for equally spaced trading days during the merger deal. The option expiration date is the earliest date after the effective date of the merger. On the x-axis we have the ratio K/B_1 (call strike price K to merger offer price B_1). On the y-axis we have the BS-implied volatility for the observed call price, using either a star or a dot: a star for an option with positive trading volume, or a dot for an option with zero volume; and the BS-implied volatility for the theoretical call price (based on the model in this paper), using a continuous solid line. The parameters used to compute the theoretical price are estimated by using each day only the option with the highest trading volume on that day.

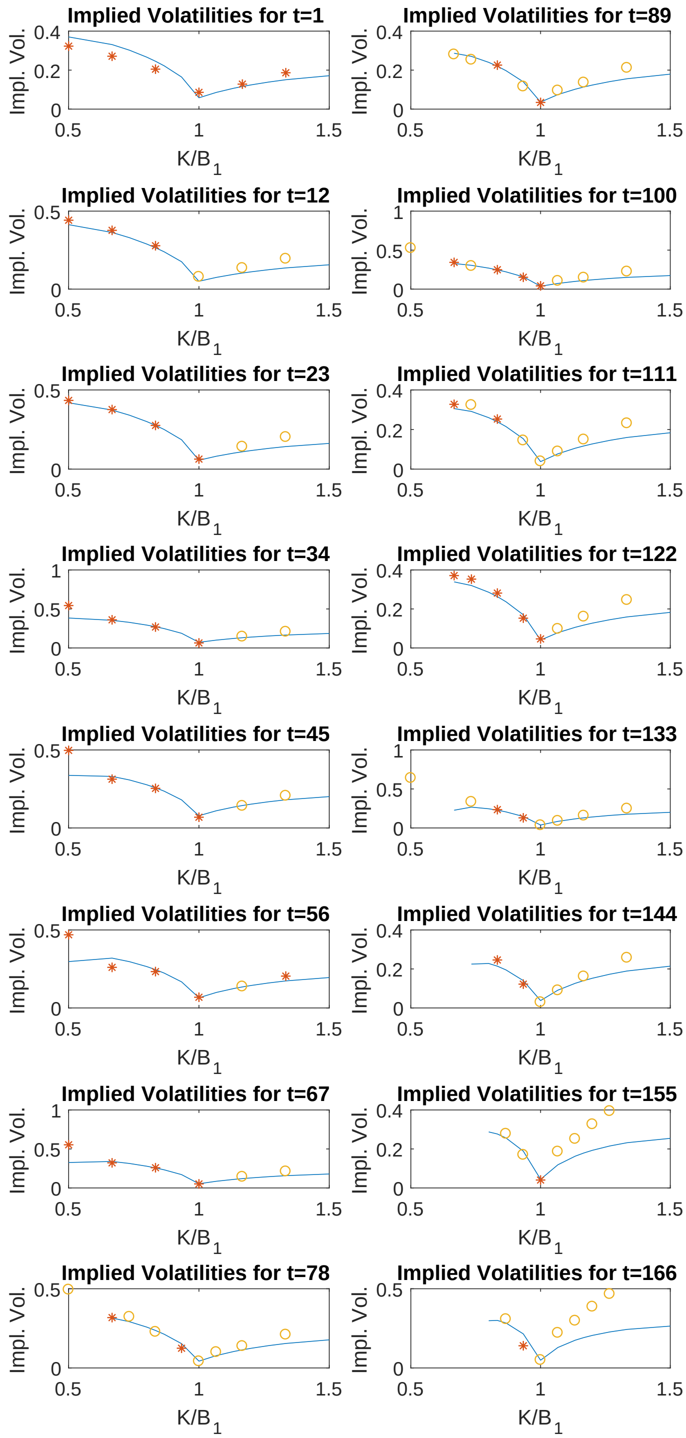

Figure 5: Pricing Calls with Expiration before the Effective Date. This figure displays pricing errors for European call options on the target company B of a merger, when the expiration date T is smaller than the merger effective date T_e. The figure compares prices compute at $t = 0$: (i) the correct price C_{correct} from equation (B5), and (ii) the "simple" price C_{simple} from equation (8) which is correct only if T is larger than T_e. On the x-axis is the time T until expiration, and on the y-axis is the pricing error $(C_{\text{simple}} - C_{\text{correct}})/C_{\text{correct}}$. The parameters used in the formulas are: $T_e = 100$ days (effective date) divided by 252 = the number of trading days in 1 year; $B_1 = 100$ (offer price); $B_2(0) = 90$ (fallback price at $t = 0$); $q(0) = 0.5$ (success probability at $t = 0$); $r = 0.05$ (annual risk-free rate); and $\sigma_2 = 0.4$ (annual fallback price volatility). The stock price at $t = 0$ corresponding to these parameters is $B(0) = 94.018$. The figure display the results when the expiration date T varies between 80 and 100 days, and the strike price K varies between 75 and 105 ($K = 95$ corresponds to the at-the-money call).

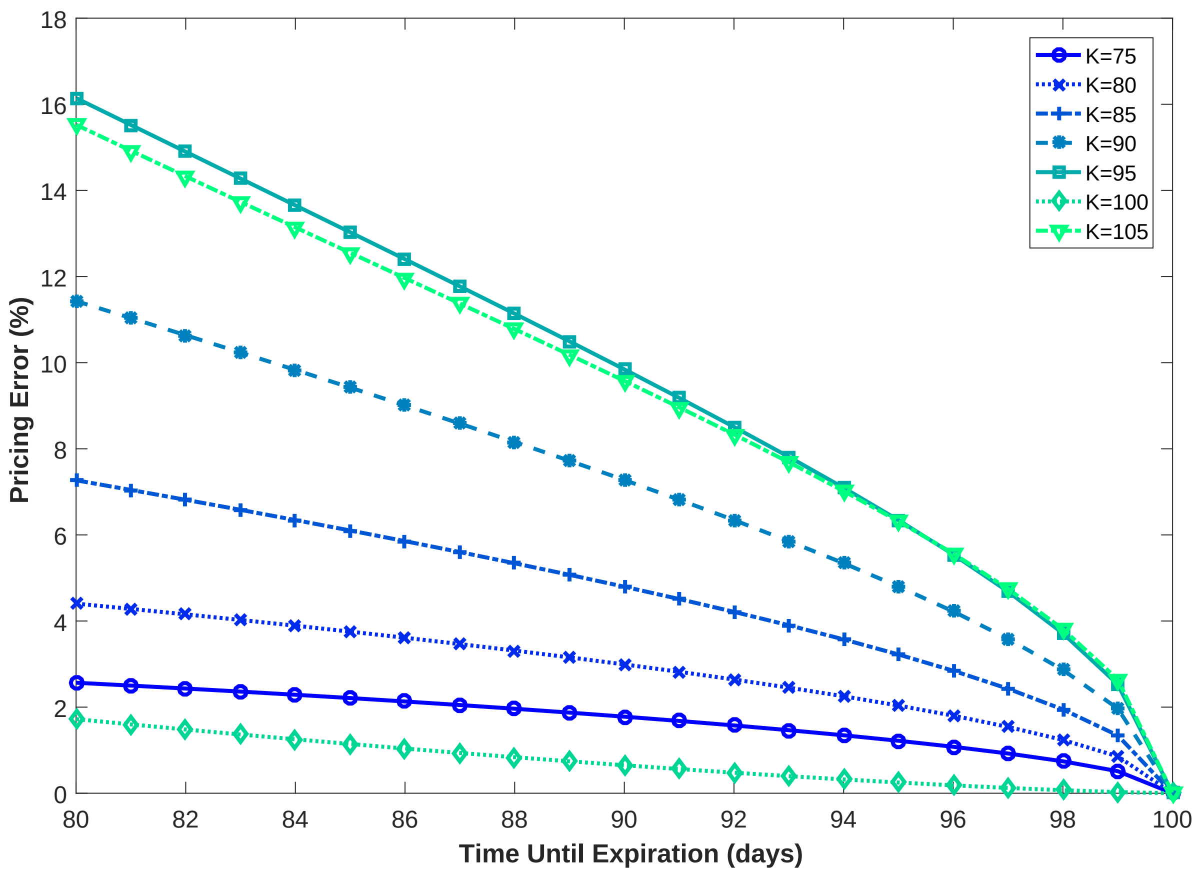

Table 1: Data Description. This table shows summary statistics for our sample of cash mergers. We include the mean, standard deviation, and various percentiles for the following variables: the number of trading days between deal announcement and deal conclusion (Deal Duration); the percentage difference between the offer price per share and the 1-day pre-announcement target share price (Offer Premium); the percentage of trading days for which there is at least one option with positive trading volume (Frac. Days Calls Traded); the average number of call option contracts (1 contract = 100 options) traded on the target company (Ave. Call Volume); the number of times the offer price changed during the merger deal (Offer Price Changes); and the number of times the merger effective date was changed during the life of the deal (Effec. Date Changes). N represents the number of firms with non-missing estimates.

			Percentile							
Variable	Mean	StDev	Min	5%	25%	50%	75%	95%	Max	N
Deal Duration (trading days)	66.6	42.5	5	25	35.5	55	84	149.9	402	812
Offer Premium (%)	33.51	37.50	-95.13	3.27	16.50	28.07	43.42	78.93	729.15	810
Frac. Days Calls Traded (%)	65.04	28.66	0	15.02	41.38	68.29	92.82	100	100	812
Ave. Call Volume	1085.4	4389.5	0	5.9	30.5	113.8	467.8	4070.6	59143.2	812
Offer Price Changes	0.13	0.43	0	0	0	0	0	1	5	812
Effec. Date Changes	0.74	1.78	0	0	0	0	1	4	21	812

Table 2: Bid-Ask Spreads of Call Options. For target company i in our sample of cash mergers, we report statistics for μ_i, which in Panel A is the average absolute bid-ask spread, and in Panel B is the relative bid-ask spread (Panel B). This average is computed over several categories of options that depend on the option's moneyness $m = K/S$ (K is the strike price and S is the underlying stock price): all calls; deep-in-the-money (Deep-ITM) calls, with $m < 0.9$; in-the-money (ITM) calls, with $m \in [0.9, 0.95)$; near-in-the-money (Near-ITM) calls, with $m \in [0.95, 1]$; near-out-the-money (Near-OTM) calls, with $m \in [1, 1.05]$; out-of-the-money (OTM) calls, with $m \in (1.05, 1.1]$; and deep-out-of-the-money (Deep-OTM) calls if $m > 1.1$. Entries with zero bid-ask spread or zero bid price are considered missing. N is the number of target firms with at least one non-missing estimate.

A. Absolute Bid-Ask Spread ($)

Selection	Mean	StDev	Min	5%	25%	50%	75%	95%	Max	N
			Percentile							
All Calls	1.08	0.98	0.05	0.23	0.41	0.71	1.36	3.48	4.78	804
Deep-ITM Calls	1.26	1.09	0.15	0.29	0.47	0.84	1.66	3.78	4.83	790
ITM Calls	0.79	0.80	0.08	0.17	0.28	0.49	0.92	2.51	4.58	568
Near-ITM Calls	0.54	0.55	0.04	0.11	0.23	0.35	0.63	1.72	4.31	528
Near-OTM Calls	0.37	0.43	0.03	0.06	0.14	0.24	0.41	1.15	3.92	549
OTM Calls	0.36	0.44	0.03	0.06	0.14	0.23	0.40	1.00	4.95	465
Deep-OTM Calls	0.38	0.57	0.03	0.05	0.14	0.22	0.41	1.11	4.95	487

B. Relative Bid-Ask Spread (%)

Selection	Mean	StDev	Min	5%	25%	50%	75%	95%	Max	N
			Percentile							
All Calls	27.46	20.00	3.76	8.64	14.79	22.06	33.28	66.22	195.70	804
Deep-ITM Calls	17.29	15.94	2.25	4.53	7.88	12.28	20.53	50.30	145.11	790
ITM Calls	28.50	23.78	4.54	7.51	13.51	21.04	35.58	74.73	163.64	568
Near-ITM Calls	41.22	29.84	6.13	11.09	19.87	31.61	53.81	106.37	160.00	528
Near-OTM Calls	74.92	35.67	8.09	21.06	49.36	72.22	97.19	137.73	181.81	549
OTM Calls	85.16	35.73	5.77	26.52	59.62	86.23	112.78	139.01	196.04	465
Deep-OTM Calls	94.93	34.49	5.37	39.01	67.87	93.15	119.23	154.81	196.04	487

Table 3: Ten Selected Cash Mergers. This table shows information for 10 large deals sorted on offer value (offer price per share times the target's number of shares outstanding). From our sample of cash mergers with options traded on the target company, we select the five largest deals that succeeded, and the five largest deals that failed. Panel A shows the names of the acquirer and target company, the ticker of the target company, and the offer value in billion U.S. dollars. Panel B shows the target's ticker, the deal announcement date, the date when the deal succeeded or failed, the target's stock price one day before the announcement $B(0)$, the offer price B_1, and the offer premium, i.e., the percentage change $\big(B_1 - B(0)\big)/B(0)$.

A. List of Deals

Acquirer Name	Target Name	Tgt.Ticker	Offer Value ($ bn)
InBev NV	Anheuser-Busch Cos Inc	BUD	49.92
Cingular Wireless LLC	AT&T Wireless Services Inc	AWE	40.72
TXU Corp SPV	TXU Corp	TXU	31.80
Atlantis Holdings LLC	Alltel Corp	AT	25.76
Kohlberg Kravis Roberts & Co	First Data Corp	FDC	25.60
Investor Group	SLM Corp	SLM	24.53
GTE Corp	MCI Communications Corp	MCIC	22.24
China National Offshore Oil	Unocal Corp	UCL	18.20
Penn National Gaming Inc	Harrahs Entertainment Inc	HET	16.17
Coty US Inc	Avon Products Inc	AVP	10.67

B. Deal Information

Target Ticker	Date Announced	Date Ended	Deal Status	Price 1 Day. Before Ann.	Offer Price ($)	Offer Premium (%)
BUD	6/11/2008	11/18/2008	Completed	50.23	70	37.56
AWE	2/17/2004	10/26/2004	Completed	8.55	15	75.44
TXU	2/26/2007	10/10/2007	Completed	57.64	69.25	20.14
AT	5/20/2007	11/16/2007	Completed	58.19	71.5	22.87
FDC	4/2/2007	9/24/2007	Completed	26.90	34	26.39
SLM	4/16/2007	12/13/2007	Withdrawn	40.75	60	47.24
MCIC	10/15/1997	12/17/1997	Withdrawn	25.13	40	59.20
UCL	6/22/2005	8/2/2005	Withdrawn	44.34	67	51.11
HET	12/12/2006	12/19/2006	Withdrawn	78.46	87	10.88
AVP	4/2/2012	5/14/2012	Withdrawn	18.52	24.75	26.51

Table 4: Success Probability as Predictor of Deal Outcome. For target company i in our sample of cash mergers, let $q_i(t)$ be the success probability estimated at date t using only one option per day (with the highest trading volume). Also, let $q_i^{\text{naive}}(t)$ be the naive success probability, computed as the ratio $\big(S_i(t) - S_i(0)\big)/\big(S_i^{\text{offer}} - S_i(0)\big)$, where $S_i(t)$ is the current stock price, $S_i(0)$ is the stock price one day before the merger announcement, S_i^{offer} is the offer price, and the ratio is truncated to be in the interval $(0, 1)$. Each column corresponds to a probit cross-sectional regression in which the dependent variables is the outcome of the merger deal (success or failure) and the independent variables are q or q^{naive}, averaged out over the duration of the deal. The control variables are: "Same Industry" (the industry is one of the 13 macro industries defined by SDC), "Intrastate" (the acquirer and target are in the same U.S. state), "Foreign Acquirer" (the acquirer is a non U.S.-based firm), "Public Acquirer" (the acquirer is a public company), "Transaction Value" (the deal's transaction value, natural logarithm), "Price Increase" (the target company's price increase from the lowest price during the last 12 months to the price 1 day before the merger announcement), "Prior Held" (dummy variable equal to 1 if the acquirer holds more than 5% of the target before the announcement date), "Multiple Bidders" (dummy variable equal to 1 if there are multiple bidders for the target company), "Defense" (dummy variable equal to 1 if the target used a defense mechanism), and "Recession" (dummy variable equal to 1 if the merger announcement date corresponds to an NBER recession). The z-statistics are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
q	6.806	6.866	6.458	6.356					5.982	6.032	5.660	5.610
	(12.77)	(12.29)	(10.55)	(10.83)					(10.62)	(10.16)	(8.77)	(9.18)
q^{naive}					2.935	3.149	3.262	2.794	1.982	2.110	2.423	1.992
					(11.87)	(11.22)	(9.36)	(9.34)	(6.38)	(6.04)	(5.56)	(5.30)
Same Industry			0.384	0.367			0.237	0.233			0.366	0.332
			(1.87)	(1.91)			(1.28)	(1.39)			(1.59)	(1.61)
Intrastate			0.100	0.090			-0.018	-0.047			-0.097	-0.107
			(0.37)	(0.35)			(-0.08)	(-0.21)			(-0.33)	(-0.39)
Foreign Acquirer			0.311	0.310			0.176	0.229			0.108	0.153
			(1.21)	(1.29)			(0.80)	(1.13)			(0.39)	(0.61)
Public Acquirer			0.242	0.292			0.038	0.055			-0.065	0.037
			(1.12)	(1.44)			(0.20)	(0.31)			(-0.26)	(0.16)
Merger Premium			0.443	0.366			0.151	0.102			0.128	0.030
			(1.22)	(1.12)			(0.45)	(0.33)			(0.35)	(0.09)
Transaction Value			0.098	0.088			0.001	0.016			0.059	0.048
			(1.22)	(1.21)			(0.02)	(0.28)			(0.71)	(0.64)
Price Increase			0.964	0.486			1.613	1.100			1.151	0.501
			(1.61)	(0.92)			(3.04)	(2.35)			(1.79)	(0.89)
Prior Held			-0.315	-0.308			-0.886	-0.758			-0.433	-0.357
			(-1.03)	(-1.06)			(-3.34)	(-3.09)			(-1.34)	(-1.18)
Multiple Bidders			-1.289	-1.057			-1.541	-1.305			-1.593	-1.266
			(-4.34)	(-3.97)			(-6.11)	(-5.72)			(-5.02)	(-4.53)
Defense			-0.802	-0.711			-0.714	-0.664			-0.767	-0.652
			(-2.63)	(-2.52)			(-2.79)	(-2.88)			(-2.38)	(-2.26)
Recession				-0.887				-0.833				-0.721
				(-3.48)				(-3.78)				(-2.61)
Const.	-2.310	-1.671	-2.833	-2.980	-1.163	-1.297	-1.447	-1.299	-3.475	-3.060	-3.800	-3.632
	(-8.82)	(-1.58)	(-2.35)	(-4.48)	(-5.81)	(-2.01)	(-1.75)	(-2.64)	(-9.95)	(-2.59)	(-2.94)	(-5.24)
Year FE	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES	NO
N	812	812	798	798	810	810	798	798	810	810	798	798
Pseudo-R^2	46.45%	49.56%	57.25%	54.60%	25.39%	29.92%	43.72%	38.71%	53.22%	55.79%	62.99%	59.52%

Table 5: Call Price Kink and Success Probability. This table shows the results of panel regressions of the call price kink on the success probability. For each target company in our sample of cash mergers, consider the call options expiring at the earliest date after the effective date of the merger T_e. Define the call price kink C^{kink} as the difference between the right slope and the left slope at the strike price K nearest to the merger offer price. Let $q_{\text{norm}}(t)$ be our success probability measure discounted by the term $\mathrm{e}^{r(T_e-t)}$, where r is the risk-free rate interpolated from the yield curve. The same variables are written with a "tilde" ($\tilde{C}^{\text{kink}}$ and $\tilde{q}_{\text{norm}}$) if their values are truncated to be in the interval $(0,1)$ and inverted via the standard normal CDF function. Time fixed effects are at the period level, where the period corresponding to date t is given by $\lceil 10t/T_e \rceil$, and T_e is the effective date of the merger (there are 10 periods for each firm). Standard errors are clustered by firm. For each coefficient, the corresponding t-statistic is in parentheses, and in square brackets is the F-statistic for testing whether the coefficient is equal to 1.

	C^{kink}	C^{kink}	C^{kink}	C^{kink}	$\tilde{C}^{\text{kink}}$	$\tilde{C}^{\text{kink}}$	$\tilde{C}^{\text{kink}}$	$\tilde{C}^{\text{kink}}$
q_{norm}	0.708	0.549	0.697	0.529				
	(13.71)	(12.03)	(13.24)	(11.21)				
	[31.96]	[97.30]	[33.24]	[99.73]				
$\tilde{q}_{\text{norm}}$					0.961	0.808	0.949	0.788
					(11.72)	(10.67)	(11.26)	(9.77)
					[0.22]	[6.43]	[0.37]	[6.91]
const.	0.229	0.321	0.236	0.333	0.294	0.327	0.296	0.331
	(6.74)	(12.16)	(6.78)	(12.21)	(5.39)	(19.84)	(5.39)	(18.89)
Firm FE	NO	YES	NO	YES	NO	YES	NO	YES
Time FE	NO	NO	YES	YES	NO	NO	YES	YES
N	41,534	41,532	41,534	41,532	41,534	41,532	41,534	41,532
Clusters	683	681	683	681	683	681	683	681
R^2	8.92%	43.78%	9.14%	43.96%	9.21%	52.15%	9.42%	52.32%

Table 6: Return Volatility and Success Probability. For target company i in our sample of cash mergers, we divide the time interval between the merger announcement date ($t = 1$) and the effective date ($t = T_e$) into five integer periods as follows: if $\tau = \lfloor T_e/5 \rfloor$, let $I_1 = [1, \tau]$, $I_2 = [\tau + 1, 2\tau]$, $I_3 = [2\tau + 1, 3\tau]$, $I_2 = [3\tau + 1, 4\tau]$, and $I_5 = [4\tau + 1, T_e]$, where each integer in I_k is a trading day. Let $\sigma_{B,i,k}$ be the return volatility of firm i, measured as the standard deviation of i's daily stock return over the interval I_k, $k \in \{1, 2, 3, 4, 5\}$. If $q_i(t)$ is the success probability estimated at t using only one option per day (with the highest trading volume), denote by $q_{i,k}$ the average success probability over $t \in I_k$. Panel A shows the results of panel regressions of the return volatility σ_B on $1 - q$, where q is the success probability. Time fixed effects are at the period level. Standard errors are clustered by firm. Panel B shows the results of cross-sectional regressions of σ_B on the time-series average $1 - q$, the volatility estimates σ_q and σ_2 from, respectively, $\mathrm{d}q/\big(q(1-q)\big) = \mu_q \mathrm{d}t + \sigma_q \mathrm{d}W_q$ and $\mathrm{d}B_2/B_2 = \mu_2 \mathrm{d}t + \sigma_2 \mathrm{d}W_2$, and the merger offer premium, $\pi = \big(B_1 - B(0)\big)/B(0)$. The t-statistics are in parentheses.

A. Panel Regressions

	σ_B (%)	σ_B (%)	σ_B (%)	σ_B (%)
$1 - q$	1.519	2.737	1.389	2.147
	(5.45)	(6.40)	(4.79)	(4.86)
const.	0.415	-0.167	0.465	0.169
	(3.43)	(-0.37)	(3.72)	(0.98)
Firm FE	NO	YES	NO	YES
Time FE	NO	NO	YES	YES
N	4,060	4,060	4,060	4,060
Clusters	812	812	812	812
R^2	1.47%	31.12%	5.49%	34.98%

B. Cross-Sectional Regressions

	$\ln(\sigma_B)$	$\ln(\sigma_B)$	$\ln(\sigma_B)$	$\ln(\sigma_B)$	$\ln(\sigma_B)$	$\ln(\sigma_B)$
$1 - q$	0.942		1.581		0.921	1.597
	(3.99)		(7.80)		(3.90)	(7.93)
σ_q		0.071	0.079			0.080
		(15.11)	(16.89)			(17.22)
σ_2		0.183	0.175			0.252
		(6.30)	(6.24)			(7.19)
π				0.255	0.243	-0.445
				(2.17)	(2.08)	(-3.61)
const.	-5.443	-5.482	-6.131	-5.162	-5.518	-6.026
	(-53.26)	(-121.17)	(-65.30)	(-87.28)	(-50.84)	(-61.61)
N	812	812	812	810	810	810
R^2	1.93%	25.49%	30.62%	0.45%	2.18%	31.68%

Table 7: Relative Pricing Errors for the Stock Price. For target company i in our sample of cash mergers, this table shows statistics for μ_i, the time series average of the relative stock pricing error. On trading day t, the relative pricing error is $(S_i^{\text{BMR}}(t) - S_i(t))/S_i(t)$, where $S_i(t)$ is the target company's observed stock price, and $S_i^{\text{BMR}}(t)$ is the theoretical stock price (based on the model in this paper). The parameters used to compute the theoretical price are estimated by using each day only the option with the highest trading volume on that day. We winsorize the pricing error at 100% (for one merger deal the average pricing error is 130.89%). N is the number of firms with non-missing estimates.

			Percentile							
	Mean	StDev	Min	5%	25%	50%	75%	95%	Max	N
Pricing Error (%)	0.149	0.358	0.001	0.003	0.009	0.032	0.122	0.653	3.511	811

Table 8: Pricing Errors for Call Options. This table shows relative pricing errors, measured in percentage points, for call options traded on the target company in our sample of cash mergers. We consider only call options with the earliest expiration date after the merger effective date. For target company i, the table shows statistics for μ_i, the average relative pricing error for call options traded on i. This average is computed over several categories of options that depend on the option's moneyness $m = K/S$ (K is the strike price and S is the underlying stock price): all calls; deep-in-the-money (Deep-ITM) calls, with $m < 0.9$; in-the-money (ITM) calls, with $m \in [0.9, 0.95)$; near-in-the-money (Near-ITM) calls, with $m \in [0.95, 1]$; near-out-the-money (Near-OTM) calls, with $m \in [1, 1.05]$; out-of-the-money (OTM) calls, with $m \in (1.05, 1.1]$; and deep-out-of-the-money (Deep-OTM) calls if $m > 1.1$. On each day t, we require the first category (all calls) to have at least six (quoted) options, and the other categories (calls of a given moneyness) to have at least two options, otherwise we declare as missing the pricing errors on that day. The (relative) error is defined as $\left|\left(C^{\text{theory}}(t) - C(t)\right)/C(t)\right|$, where $C(t)$ is the observed call price (the bid-ask mid-quote), $C^{\text{BMR}}(t)$ is the theoretical call price computed using our model, and $C^{\text{BS}}(t)$ is the theoretical call price computed using the BS model, where the volatility parameter is constant for each firm and is equal to the average of the at-the-money BS-implied volatility over time. The parameters used to compute the BMR theoretical price are estimated by using each day only the option with the highest trading volume on that day. N is the number of firms with non-missing estimates.

Selection	Model	Mean	StDev	Percentile							N
				Min	5%	25%	50%	75%	95%	Max	
All Calls	BMR	9.39	10.65	0.35	1.41	3.35	6.06	11.59	27.69	72.88	243
	BS	19.49	36.92	0.51	1.74	3.94	8.14	19.13	68.61	385.95	243
Deep-ITM Calls	BMR	2.61	10.63	0.20	0.46	0.88	1.42	2.25	5.68	268.44	712
	BS	2.83	10.54	0.27	0.49	0.98	1.58	2.84	6.72	270.32	712
ITM Calls	BMR	6.97	9.18	1.55	1.68	3.45	4.84	7.41	17.01	69.10	58
	BS	9.26	9.21	1.73	2.12	4.85	7.13	10.60	21.57	67.76	58
Near-ITM Calls	BMR	12.95	12.03	2.67	3.13	7.27	10.10	13.86	32.13	85.29	58
	BS	20.33	13.37	4.12	7.21	10.72	16.70	27.62	44.13	78.40	58
Near-OTM Calls	BMR	40.62	50.73	4.97	6.84	13.85	30.84	49.23	89.76	338.46	46
	BS	98.17	116.87	8.86	12.67	35.06	56.37	72.62	386.70	536.47	46
OTM Calls	BMR	41.66	29.18	10.47	12.17	19.80	30.81	57.59	99.01	100.92	27
	BS	95.08	129.40	11.61	17.34	34.12	65.80	92.07	472.63	600.32	27
Deep-OTM Calls	BMR	66.90	66.40	12.47	17.50	36.91	56.50	77.97	136.17	564.92	128
	BS	84.17	67.42	7.10	21.86	50.33	82.09	99.52	147.76	607.71	128

Table 9: Ratio of Absolute Call Option Pricing Errors to Bid-Ask Spread. For target company i in our sample of cash mergers, this table shows statistics for μ_i, the average ratio of the absolute option pricing error to the option bid-ask spread. This average is computed over several categories of options that depend on the option's moneyness $m = K/S$ (K is the strike price, and S is the underlying stock price): all calls; deep-in-the-money (Deep-ITM) calls, with $m < 0.9$; in-the-money (ITM) calls, with $m \in [0.9, 0.95)$; near-in-the-money (Near-ITM) calls, with $m \in [0.95, 1]$; near-out-the-money (Near-OTM) calls, with $m \in [1, 1.05]$; out-of-the-money (OTM) calls, with $m \in (1.05, 1.1]$; and deep-out-of-the-money (Deep-OTM) calls if $m > 1.1$. The absolute pricing error is the difference $|C^{\text{theory}}(t) - C^{\text{obs}}(t)|$ between the theoretical price computed using our model and the observed call price. The parameters used to compute the theoretical price are estimated by using each day only the option with the highest trading volume on that day. N represents the number of firms with non-missing estimates.

			Percentile							
Selection	Mean	StDev	Min	5%	25%	50%	75%	95%	Max	N
All Calls	0.37	0.50	0.07	0.16	0.24	0.30	0.39	0.72	11.55	794
Deep-ITM Calls	0.22	0.65	0.00	0.04	0.09	0.14	0.22	0.50	13.17	779
ITM Calls	0.47	0.93	0.00	0.08	0.17	0.30	0.49	1.26	18.54	561
Near-ITM Calls	0.64	1.08	0.00	0.13	0.26	0.43	0.69	1.86	21.31	550
Near-OTM Calls	0.72	1.06	0.01	0.15	0.33	0.48	0.70	2.08	16.28	567
OTM Calls	0.65	0.77	0.01	0.19	0.37	0.50	0.65	1.78	12.51	535
Deep-OTM Calls	0.55	0.31	0.13	0.34	0.46	0.50	0.50	1.02	3.81	709

Table 10: Pricing Errors for Put Options. This table shows relative pricing errors, measured in percentage points, for put options traded on the target company in our sample of cash mergers. We consider only put options with the earliest expiration date after the merger effective date. For target company i, the table shows statistics for μ_i, the average relative pricing error for put options traded on i. This average is computed over several categories of options that depend on the option's moneyness $m = S/K$ (S is the underlying stock price, and K is the strike price): all puts; deep-in-the-money (Deep-ITM) puts, with $m < 0.9$; in-the-money (ITM) puts, with $m \in [0.9, 0.95)$; near-in-the-money (Near-ITM) puts, with $m \in [0.95, 1]$; near-out-the-money (Near-OTM) puts, with $m \in [1, 1.05]$; out-of-the-money (OTM) puts, with $m \in (1.05, 1.1]$; and deep-out-of-the-money (Deep-OTM) puts if $m > 1.1$. On each day t we require the first category (all puts) to have at least six (quoted) options, and the other categories (puts of a given moneyness) to have at least two options, otherwise we declare as missing the pricing errors on that day. The (relative) error is defined as $\left|\left(P^{\text{theory}}(t) - P(t)\right)/P(t)\right|$, where $P(t)$ is the observed put price (the bid-ask mid-quote), $P^{\text{BMR}}(t)$ is the theoretical European put price computed using our model; and $P^{\text{BS}}(t)$ is the theoretical European put price computed using the BS model, where the volatility parameter is constant for each firm and is equal to the average of the at-the-money BS-implied volatility over time. The parameters used to compute the BMR theoretical price are estimated by using each day only the option with the highest trading volume on that day. N is the number of firms with non-missing estimates.

							Percentile				
Selection	Model	Mean	StDev	Min	5%	25%	50%	75%	95%	Max	N
All Puts	BMR	31.58	30.11	1.33	5.23	14.43	24.45	43.60	72.26	392.93	264
	BS	38.29	31.62	1.53	6.15	17.53	35.20	55.33	73.53	403.85	264
Deep-ITM Puts	BMR	5.35	27.22	0.16	0.40	0.97	2.22	4.41	13.62	551.61	434
	BS	5.35	27.26	0.16	0.41	0.95	2.35	4.52	15.15	558.82	434
ITM Puts	BMR	29.16	184.92	0.65	0.93	2.29	5.08	7.51	19.20	1484.73	64
	BS	30.53	191.99	0.71	0.95	2.46	4.84	8.11	20.54	1541.74	64
Near-ITM Puts	BMR	15.34	9.17	3.92	5.05	9.82	13.10	17.89	33.56	52.84	61
	BS	23.99	26.94	3.21	5.86	9.65	15.81	24.41	76.46	175.56	61
Near-OTM Puts	BMR	41.37	23.91	7.64	8.58	20.81	37.48	66.47	79.06	89.73	52
	BS	54.70	22.60	11.19	17.41	42.67	53.43	65.36	98.33	102.52	52
OTM Puts	BMR	53.60	32.54	9.77	9.84	26.70	49.09	82.78	100.00	111.23	34
	BS	77.23	28.95	14.20	24.26	60.84	85.03	96.99	100.00	153.66	34
Deep-OTM Puts	BMR	74.47	26.04	8.62	25.92	53.65	82.63	99.19	100.00	104.13	321
	BS	89.39	18.48	16.39	47.07	85.81	98.56	99.97	100.00	151.78	321