ONLINE APPENDIX A: Numerical Estimation

Although the target's market value V_0^M and the target's value as seen by the diligent acquirer V_0^D are estimated numerically, this estimation is a quasi-analytical procedure rather than a Monte-Carlo simulation. Instead of simulating multiple paths for a stochastic process, the procedure is based on the efficient approximation of the continuous-time geometric Brownian motion with a discrete-time binomial process that was developed by Cox et al. (1979) for the estimation of univariate options and extended by Boyle et al. (1989) to bivariate options. This transformation, used in thousands of studies, preserves the first two moments of the original continuous-time probability distribution and returns an accurate value estimate provided the number of time discretization steps N is sufficiently large. In particular, to estimate V_0^M and of V_0^D, the continuous-time geometric Brownian processes for margins C_{it} and C_{jt} specified with Equations 1–3 are approximated with the discrete-time binomial lattice, where the next-period margins $C_{it+\partial t}$ and $C_{jt+\partial t}$ take one of four states: $C_{it+\partial t}^u$ and $C_{jt+\partial t}^u$ with probability q^{uu}, $C_{it+\partial t}^u$ and $C_{jt+\partial t}^d$ with probability q^{ud}; $C_{it+\partial t}^d$ and $C_{jt+\partial t}^u$ with probability q^{du}; or $C_{it+\partial t}^d$ and $C_{jt+\partial t}^d$ with probability q^{dd} (Boyle et al. 1989). With N discretization steps each of the length $\partial t = T/N$, values of the margins in the immediate next time are assessed as follows:

$$C_{it+\partial t}^u = u_i C_{it} \qquad \text{(A1)}$$

$$C_{it+\partial t}^d = d_i C_{it} \qquad \text{(A2)}$$

$$C_{jt+\partial t}^u = u_j C_{jt} \qquad \text{(A3)}$$

$$C_{jt+\partial t}^d = d_j C_{jt}\ , \qquad \text{(A4)}$$

where

$$u_i = e^{\sigma_i \sqrt{\partial t}} \qquad \text{(A5)}$$

$$d_i = 1/u_i \qquad \text{(A6)}$$

$$u_j = e^{\sigma_j \sqrt{\partial t}} \qquad \text{(A7)}$$

$$d_j = 1/u_j\ . \qquad \text{(A8)}$$

Transition probabilities on the binomial lattice for the margins are calculated as follows:

$$q^{uu} = \frac{1}{4}\left[1+\sqrt{\partial t}\left(\frac{r-\frac{1}{2}\sigma_i^2}{\sigma_i}+\frac{r-\frac{1}{2}\sigma_j^2}{\sigma_j}\right)\right] \qquad \text{(A9)}$$

$$q^{ud} = \frac{1}{4}\left[1+\sqrt{\partial t}\left(\frac{r-\frac{1}{2}\sigma_i^2}{\sigma_i}-\frac{r-\frac{1}{2}\sigma_j^2}{\sigma_j}\right)\right] \qquad \text{(A10)}$$

$$q^{du} = \frac{1}{4}\left[1+\sqrt{\partial t}\left(-\frac{r-\frac{1}{2}\sigma_i^2}{\sigma_i}+\frac{r-\frac{1}{2}\sigma_j^2}{\sigma_j}\right)\right] \qquad \text{(A11)}$$

$$q^{dd} = \frac{1}{4}\left[1+\sqrt{\partial t}\left(-\frac{r-\frac{1}{2}\sigma_i^2}{\sigma_i}-\frac{r-\frac{1}{2}\sigma_j^2}{\sigma_j}\right)\right]. \qquad \text{(A12)}$$

Similarly, the immediate-next-time values of the marginal redeployment cost and of the sharing factor as seen by a representative buyer are assessed as follows:

$$S_{t+\partial t}^{uM} = u_M S_t^M \qquad \text{(A13)}$$

$$S_{t+\partial t}^{dM} = d_M S_t^M \qquad \text{(A14)}$$

$$\beta_{t+\partial t}^{uM} = u_M \beta_t^M \qquad \text{(A15)}$$

$$\beta_{t+\partial t}^{dM} = d_M \beta_t^M , \qquad \text{(A16)}$$

where

$$u_M = e^{\sigma_M \sqrt{\partial t}} \qquad \text{(A17)}$$

$$d_M = 1/u_M . \qquad \text{(A18)}$$

Likewise, the immediate-next-time values of the marginal redeployment cost and of the sharing factor as seen by the diligent acquirer are assessed as follows:

$$S_{t+\partial t}^{uD} = u_D S_t^D \qquad \text{(A19)}$$

$$S_{t+\partial t}^{dD} = d_D S_t^D \qquad \text{(A20)}$$

$$\beta_{t+\partial t}^{uD} = u_M \beta_t^D \qquad \text{(A21)}$$

$$\beta_{t+\partial t}^{dD} = d_M \beta_t^D , \qquad \text{(A22)}$$

where

$$u_D = e^{\sigma_D \sqrt{\partial t}} \qquad \text{(A23)}$$

$$d_D = 1/u_D . \qquad \text{(A24)}$$

The method based on the ‘maxmin’ principle of Gilboa and Schmeidler (1989) does not require the knowledge of the transition probabilities for S_t^M , β_t^M , S_t^D , or β_t^D .

Then, the principle of dynamic optimality (Bellman 1957) is used to compute the target’s market valuation V_t^M and the targets value as seen by the diligent acquirer V_t^D at time t under the known probability distribution:

$$V_t^{xyM} = \max_{\phi_{it}^{xy}}\{F_t^{xyM}(\phi_{it}^{xy}) + e^{-r\partial t}[q^{uu}V_{t+\partial t}^{uuM}\left|\phi_{it}^{xy*}\right. + q^{ud}V_{t+\partial t}^{udM}\left|\phi_{it}^{xy*}\right. + q^{du}V_{t+\partial t}^{duM}\left|\phi_{it}^{xy*}\right. + q^{dd}V_{t+\partial t}^{ddM}\left|\phi_{it}^{xy*}\right.]\}. \qquad \text{(A25)}$$

$$V_t^{xyD} = \max_{\omega_{it}^{xy}}\{F_t^{xyD}(\psi_{it}^{xy}) + e^{-r\partial t}[q^{uu}V_{t+\partial t}^{uuD}\left|\psi_{it}^{xy*}\right. + q^{ud}V_{t+\partial t}^{udD}\left|\psi_{it}^{xy*}\right. + q^{du}V_{t+\partial t}^{duD}\left|\psi_{it}^{xy*}\right. + q^{dd}V_{t+\partial t}^{ddD}\left|\psi_{it}^{xy*}\right.]\}. \qquad \text{(A26)}$$

In Equation A25, $V_{t+\partial t}^{uuM}\left|\phi_{it}^{xy*}\right.$, $V_{t+\partial t}^{udM}\left|\phi_{it}^{xy*}\right.$, $V_{t+\partial t}^{duM}\left|\phi_{it}^{xy*}\right.$, and $V_{t+\partial t}^{ddM}\left|\phi_{it}^{xy*}\right.$ capture four possible realizations of the target’s market value (corresponding to the four possible realizations of C_{it+1} and C_{jt+1} on the lattice) at the immediate next time $t+\partial t$ that are conditioned on a current choice ϕ_{it}^{xy*} made by a representative buyer and are weighted by their respective probabilities. In Equation A26, $V_{t+\partial t}^{uuD} \left| \psi_{it}^{xy*} \right.$, $V_{t+\partial t}^{udD} \left| \psi_{it}^{xy*} \right.$, $V_{t+\partial t}^{duD} \left| \psi_{it}^{xy*} \right.$, and $V_{t+\partial t}^{ddD} \left| \psi_{it}^{xy*} \right.$ capture four possible realizations of the immediate-next-time target's value as seen by the diligent acquirer that are conditioned on a current choice, ψ_{it}^{xy*} made by the focal acquirer and are weighted by their respective probabilities. (Optimal current choices ϕ_{it}^{xy*} and ψ_{it}^{xy*} can differ between Equations A25 and A26.) Wherever superscript M is combined with subscript t for $F(\cdot)$ (or with subscript $t+1$ for $V(\cdot)$) in Equation A25, the lowest possible value of β_t^M (or β_{t+1}^M) and the highest possible value of S_t^M (or S_{t+1}^M) on their respective lattice at time t (or $t+1$) should be used to reflect the worst-case scenario as per Gilboa and Schmeidler (1989). Likewise, wherever superscript M is combined with subscript t for $F(\cdot)$ (or with subscript $t+1$ for $V(\cdot)$) in Equation A26, the lowest possible value of β_t^D (or β_{t+1}^D) and the highest possible value of S_t^D (or S_{t+1}^D) on their respective lattice at time t (or $t+1$) should be used to reflect the worst-case scenario as per Gilboa and Schmeidler (1989). To derive present values V_0^M and V_0^D, calculation starts at time $t = T - \partial t$ with the terminal conditions $V_T^M = 0$ and $V_T^D = 0$, and proceeds recursively backward in time until it reaches the present time $t = 0$.

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ONLINE APPENDIX B: Parameter Values Used and Robustness Tests

The following parameter values are held constant in Figures 1 and 2: $C_{i0} = C_{j0} = 0.08$, $\mu_i = \mu_j = 0.08$, $\sigma_j = 0.5$, $\rho = 0$, $T = 1$, and $r = 0.08$. The number of time-discretization steps is also uniformly set to $N = 1000$.

In Figure 1, 'intra-temporal economies of scope' (Helfat & Eisenhardt 2004) from resource sharing are disallowed by setting $\beta = 0$. The only manifestation of relatedness in this figure, the marginal rtedeployment cost, varies from its lowest value ($S = 0$) to its highest value ($S = 400$), thus corresponding to the variation of relatedness from its lowest value to its highest value. Ambiguity about economies of scope varies in Figure 1 from its lowest value $(\sigma_M = 0.0)$ to its highest value $(\sigma_M = 2.1)$.

In Figure 2, 'inter-temporal economies of scope' (Helfat & Eisenhardt 2004) from resource redeployment are disallowed by precluding redeployment of the target's tresourcres to the acquirer's business; thus, the value of S is irrelevant. The only manifestation of relatedness in Figure 2, the sharing factor, varies from its lowest value ($\beta = 0.00$) to its highest value $(\beta = 0.10)$, thus corresponding to the variation of relatedness from its lowest value to its highest value. Ambiguity about economies of scope varies in Figure 2 from its lowest value $(\sigma_M = 0.0)$ to its highest value $(\sigma_M = 2.1)$.

The original specification of uncertain margins described with Equations 1–3 is taken from Sakhartov and Folta (2014) and is two-dimensional or bivariate: it involves two random variables C_{it} and C_{jt}. However, the model in the current study is more complex than in Sakhartov and Folta (2014). The complexity is added by Equations 12 and 13 that introduce the endogenous choice of the due diligence effort, which demands substantially longer computation time. Therefore, to increase the efficiency of computation, the dimensionality of the model is reduced to derive the results reported in Figures 1 and 2. In particular, these figures are created for the case $\sigma_i = 0$, wherein the margin in the target's business is time-variant but certain:

$$C_{it} = C_{i0}e^{\mu_i t}. \qquad \text{(B1)}$$

As described below, this reduction does not compromise the generality of the reported results.

The following tests have investigated the robustness of the results reported with Figures 1 and 2. First, the two-dimensional specification of uncertain margins described with Equations 1–3 is restored in Figures B1–B14; but, to make the model tractable numerically, the number of time-discretization steps is reduced to $N = 200$. Also, the model is further simplified by allowing redeployment of resources only in the direction from the target to the acquirer. As Figures B1 and B2 indicate, all the predictions that were based on Figures 1 and 2 and were summarized in Table 1 remain intact.

Second, the acquirer and the target are allowed to perform asymmetrically so that the acquirer initially outperforms ($C_{i0} = 0.07 < C_{j0} = 0.09$) or initially underperforms ($C_{i0} = 0.09 > C_{j0} = 0.07$) the target. As Figures B3–B6 show, all the predictions that were based on Figures 1 and 2 and were summarized in Table 1 keep robust.

Third, volatilities of margins in the target's and the acquirer's businesses, σ_i and σ_j respectively, are cast as low $(\sigma_i = \sigma_j = 0.1)$ and as high $(\sigma_i = \sigma_j = 0.9)$. As Figures B7–B10 display, all the predictions that were based on Figures 1 and 2 and were summarized in Table 1 still hold.

Fourth, correlation ρ of margins between the target's and the acquirer's businesses is specified as negative ($\rho = -0.5$) and as positive ($\rho = 0.5$). As Figures B11–B14 demonstrate, all the predictions that were based on Figures 1 and 2 and were summarized in Table 1 remain robust.

Fifth, because relatedness both decreases S and raises β, a strong negative relationship between S and β might occur, thus potentially making β redundant to S, even though the tentative empirical evidence has found no evidence of such strong codetermination (Sakhartov 2017; Sakhartov and Folta 2014). Besides, because relatedness increases the intensity of redeployment (Anand 2004) and of sharing (Bryce & Winter 2009) of resources, it can reduce the uniqueness of those events. Then, a strong negative relationship between relatedness and ambiguity may occur, thus potentially making σ_M redundant. The final robustness analyses responded to that issue by eliminating separate independent specification of β and of σ_M and by making β perfectly negatively determined by S and σ_M perfectly positively determined by S. Both the optimal due diligence effort and the return to the acquirer in Figure B15 reveal inverse U-shaped relationships with the resulting aggregate measure of relatedness, thus replicating the results in Figure 1.

Sixth, the model relaxes the assumption that the alternative buyer is passive and does not undertake due diligence. In this robustness test, the price for the target matches the competitive bid that the active alternative buyer makes before the focal acquirer.[1] The bid by the alternative buyer is based on due diligence effort λ that the alternative buyer commits. Because the exclusive focus of this study is on the implications of due diligence, the only way in which the alternative buyer differs from the focal acquirer is in its due diligence capability γ operationalized as follows. When the alternative buyer exerts due diligence effort $\lambda \geq 0$, that effort makes S and β less ambiguous to the alternative buyer:

$$\sigma_K = \frac{\sigma_M}{(1+\gamma\lambda)} \qquad \text{(B2)}$$

$$S_t^K = S_0^K e^{\left[\left(\mu_S - \frac{\sigma_K^2}{2}\right)t + \sigma_K W_{Kt}\right]} \qquad \text{(B3)}$$

$$\beta_t^K = \beta_0^K e^{\left[\left(\mu_\beta - \frac{\sigma_K^2}{2}\right)t + \sigma_K W_{Kt}\right]}. \qquad \text{(B4)}$$

In Equations B3 and B4, S_t^K and β_t^K reflect multiple priors that the alternative buyer maintains at time t for S and β based on the residual ambiguity σ_K.[2] The due diligence capability γ sets the ability of the alternative buyer to reduce ambiguity relative to the focal acquirer. In particular, when $\gamma = 1$, the alternative buyer is as capable at due diligence as the focal acquirer; when $0 < \gamma < 1$, the alternative buyer is less capable at due diligence than the focal acquirer; and when $\gamma > 1$, the alternative buyer is more capable at due diligence than the focal acquirer. Based on the reduction in ambiguity in due diligence, the highest price the alternative buyer is willing to pay for the target is the following:

---

[1] The results of this sixth modification do not change when the focal acquirer and the alternative bidder know due diligence capability of each other and submit their bids for the target simultaneously.

[2] The Brownian motion W_{Kt} is set uncorrelated with W_{it}, W_{jt}, W_{Mt}, or W_{Dt}. Initial values S_0^K and β_0^K for S_t^K and β_t^K are set equal to the respective true values S and β; and μ_S and μ_β are drifts for the evolution of priors for S and for β assumed to be the same as in Equations 5, 6, 10, and 11.

$$V_0^K = \max_{\Pi} \int_{t=0}^{t=T} \left[e^{-rt} \int_y \int_x \min_{z \in Q_{xyz}^K} \left\{ F_t^{xyz} \right\} dxdy \right] dt - V_0^A = \max_{\Pi} \int_{t=0}^{t=T} \left[e^{-rt} \int_y \int_x F_t^{xy\underline{Q}_{xyz}^K} dxdy \right] dt - V_0^A . \quad \text{(B.5)}$$

The 'min' in Equation B5 models ambiguity aversion of the alternative buyer, with which that buyer counts on the worst case $\underline{Q}_{xyz}^K$ from all scenarios Q_{xyz}^K for S_t^K and β_t^K : the highest value $\overline{S}_t^K$ and the lowest value $\underline{\beta}_t^K$. Choices Π with regard to the target's resources by the alternative buyer can differ from the respective choices by the focal acquirer. Equation B5 is solved with the backward induction in the same way as other Bellman equations are solved in the main model.

The disutility of the due diligence effort to the alternative buyer captures diminishing returns to the that effort in the same way as for the focal acquirer. That ramification is operationalized by setting the problem of choosing the optimal due diligence effort by the alternative buyer as follows:

$$\lambda^* = \arg\max_{\lambda} \left\{ \frac{\left(V_0^K(\lambda) - V_0^M \right)}{(1+\lambda)} \right\} \quad \text{(B6)}$$

$$\Delta_K^* = \max_{\lambda} \left\{ \frac{\left(V_0^K(\lambda) - V_0^M \right)}{(1+\lambda)} \right\}, \quad \text{(B7)}$$

where Δ_K^* is the net return to the alternative buyer that is maximized by that buyer with respect to the endogenously selected due diligence effort λ with the optimal value λ^*. With this sixth extension, the problem of choosing the optimal due diligence level by the focal acquirer changes to the following:

$$\theta^* = \arg\max_{\theta} \left\{ \frac{\left(V_0^D(\theta) - V_0^K \right)}{(1+\theta)} \right\} \quad \text{(B8)}$$

$$\Delta^* = \max_{\theta} \left\{ \frac{\left(V_0^D(\theta) - V_0^K \right)}{(1+\theta)} \right\}. \quad \text{(B9)}$$

Also, because this new model is more complex and takes two times longer to estimate than the main model, the new model allows resource redeployment only in the direction from the target to the acquirer.

Figures B16 and B17 indicate that, when the alternative buyer is at least as capable at due diligence as the focal acquirer (*i.e.*, $\gamma \geq 1$), the focal acquirer commits no due diligence effort and receives zero return. This result is expected because the focal acquirer cannot outbid the equally- or even more-capable alternative buyer. Conversely, Figures B18 and B19 show that, when the alternative is less capable at due diligence than the focal acquirer, the focal acquirer commits some due diligence effort, wins the bid, and attains some returns, at least with some configurations of the marginal redeployment cost, of the sharing factor, and of ambiguity. The main observation in Figures B18 and B19 is that these figures replicate the shapes revealed in Figures 1 and 2, thus confirming that the main simpler model generates consistent prediction and is therefore more efficient in generating theoretical predictions summarized in Table 1. This robustness is, of course, bounded by the condition that the focal acquirer should be more capable at due diligence than the alternative buyer. Another observation is that, in the new model, the focal acquirer commits higher due diligence efforts and earns lower net returns than in the main model. This result is expected in the model that changed the deal price level from V_0^M (*i.e.*, based on no due diligence by the alternative buyer) to $V_0^K \geq V_0^M$ (*i.e.*, some due diligence by that buyer).

Finally, the model relaxes the assumption that the target is passive and does not undertake any effort to resolve ambiguity and to better communicate to the market the value of economies of scope. In this robustness test, the new market price for the target that the focal acquirer should match to get the target from the market is based on the target's disambiguation effort ξ that the target commits before the bid by the acquirer. When the target commits some disambiguation effort $\xi \geq 0$, that effort makes S and β less ambiguous to the market on which the target is traded (*i.e.*, to the representative alternative buyer and to the focal acquirer before that acquirer undertakes due diligence):

$$\sigma_G = \frac{\sigma_M}{(1+\xi)} \qquad \text{(B10)}$$

$$S_t^G = S_0^G e^{\left[\left(\mu_S - \frac{\sigma_G^2}{2}\right)t + \sigma_G W_{Gt}\right]} \qquad \text{(B11)}$$

$$\beta_t^G = \beta_0^G e^{\left[\left(\mu_\beta - \frac{\sigma_G^2}{2}\right)t + \sigma_G W_{Gt}\right]}. \qquad \text{(B12)}$$

In Equations B11 and B12, S_t^G and β_t^G reflect multiple priors that market players maintain at time t for S and β based on the residual ambiguity σ_G.[3] Based on the reduction in ambiguity in due diligence, the market price for the target that the focal acquirer should match to get the target from the market is

$$V_0^G = \max_{\Lambda} \int_{t=0}^{t=T} \left[e^{-rt} \int_y \int_x \min_{z \in Q_{xyz}^G} \left\{ F_t^{xyz} \right\} dxdy \right] dt - V_0^A = \max_{\Lambda} \int_{t=0}^{t=T} \left[e^{-rt} \int_y \int_x F_t^{xy\underline{Q}_{xyz}^G} dxdy \right] dt - V_0^A. \qquad \text{(B13)}$$

The 'min' in Equation B13 models ambiguity aversion, with which market participants counts on the worst case $\underline{Q}_{xyz}^G$ from all scenarios Q_{xyz}^G for S_t^G and β_t^G: the highest value $\overline{S}_t^G$ and the lowest value $\underline{\beta}_t^G$. Choices Λ with regard to the target's resources that are assessed by the market can differ from the respective choices by the focal acquirer. Equation B13 is solved with the backward induction in the same way as other Bellman equations are solved in the main model.

The disutility of the disambiguation effort to the target captures diminishing returns to the that effort. That ramification is operationalized by setting the problem of choosing the optimal disambiguation effort by the target as follows:

$$\xi^* = \arg\max_{\xi} \left\{ \frac{\left(V_0^G(\xi) - V_0^M\right)}{(1+\xi)} \right\} \qquad \text{(B14)}$$

$$\Delta_G^* = \max_{\xi} \left\{ \frac{\left(V_0^G(\xi) - V_0^M\right)}{(1+\xi)} \right\}, \qquad \text{(B15)}$$

where Δ_G^* is the net return to the target that is maximized by that target with respect to the endogenously selected disambiguation effort ξ with the optimal value ξ^*. With this seventh extension, the problem of choosing the optimal due diligence level by the focal acquirer changes to the following:

[3] The Brownian motion W_{Gt} is set uncorrelated with W_{it}, W_{jt}, W_{Mt}, or W_{Dt}. Initial values S_0^G and β_0^G for S_t^G and β_t^G are set equal to the respective true values S and β; and μ_S and μ_β are drifts for the evolution of priors for S and for β assumed to be the same as in Equations 5, 6, 10, and 11.

$$\theta^* = \arg\max_{\theta} \left\{ \frac{\left(V_0^D(\theta) - V_0^G\right)}{(1+\theta)} \right\} \quad \text{(B16)}$$

$$\Delta^* = \max_{\theta} \left\{ \frac{\left(V_0^D(\theta) - V_0^G\right)}{(1+\theta)} \right\}. \quad \text{(B17)}$$

Also, because this new model is more complex and takes two times longer to estimate than the main model, the new model allows resource redeployment only in the direction from the target to the acquirer.

Figures B20 and B21 show that, when the target is active and commits some disambiguation effort, the focal acquirer also commits some due diligence effort, buys the target, and attains some returns, at least with some configurations of the marginal redeployment cost, of the sharing factor, and of ambiguity. The main observation in Figures B20 and B21 is that these figures fully replicate the shapes revealed in Figures 1 and 2, thus confirming that the main simpler model develops consistent prediction and is therefore more efficient in delivering predictions summarized in Table 1.

FIGURE B1

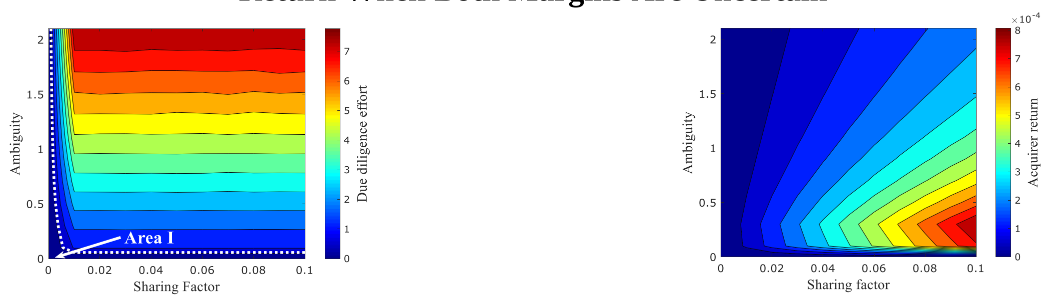
Implications of Redeployment Cost and Ambiguity for Due Diligence Effort and Acquirer Net Return When Both Margins Are Uncertain

Panel A. Optimal due diligence effort

Panel B. Acquirer net return with optimal due diligence effort

FIGURE B2

Implications of Sharing Factor and Ambiguity for Due Diligence Effort and Acquirer Net Return When Both Margins Are Uncertain

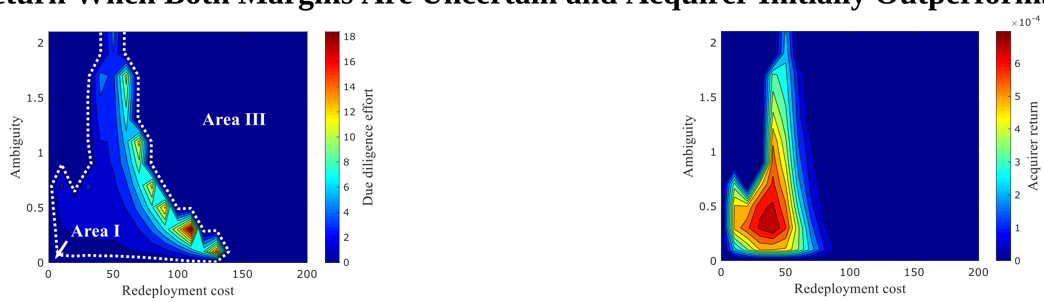


Panel A. Optimal due diligence effort

Panel B. Acquirer net return with optimal due diligence effort

FIGURE B3

Implications of Redeployment Cost and Ambiguity for Due Diligence Effort and Acquirer Net Return When Both Margins Are Uncertain and Acquirer Initially Outperforms Target



Panel A. Optimal due diligence effort

Panel B. Acquirer net return with optimal due diligence effort

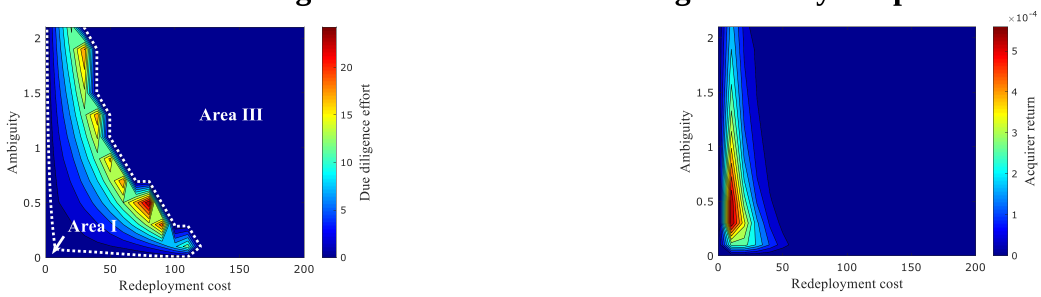
FIGURE B4

Implications of Sharing Factor and Ambiguity for Due Diligence Effort and Acquirer Net Return When Both Margins Are Uncertain and Acquirer Initially Outperforms Target

Panel A. Optimal due diligence effort **Panel B. Acquirer net return with optimal due diligence effort**

FIGURE B5

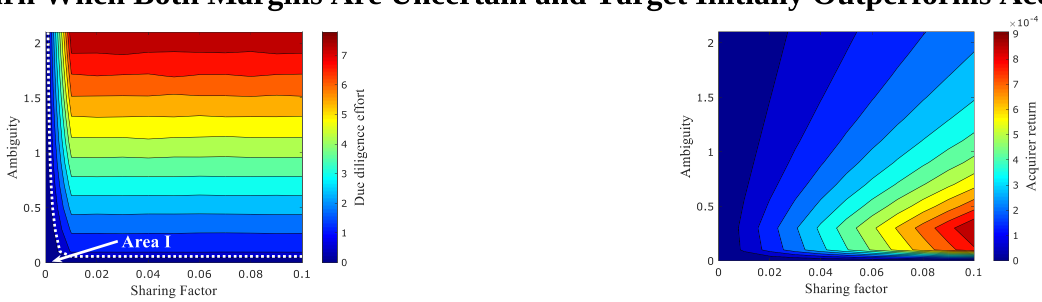
Implications of Redeployment Cost and Ambiguity for Due Diligence Effort and Acquirer Net Return When Both Margins Are Uncertain and Target Initially Outperforms Acquirer



Panel A. Optimal due diligence effort **Panel B. Acquirer net return with optimal due diligence effort**

FIGURE B6

Implications of Sharing Factor and Ambiguity for Due Diligence Effort and Acquirer Net Return When Both Margins Are Uncertain and Target Initially Outperforms Acquirer



Panel A. Optimal due diligence effort **Panel B. Acquirer net return with optimal due diligence effort**

FIGURE B7

Implications of Redeployment Cost and Ambiguity for Due Diligence Effort and Acquirer Net Return When Both Margins Are Uncertain and Have Low Volatility

Panel A. Optimal due diligence effort

Panel B. Acquirer net return with optimal due diligence effort

FIGURE B8

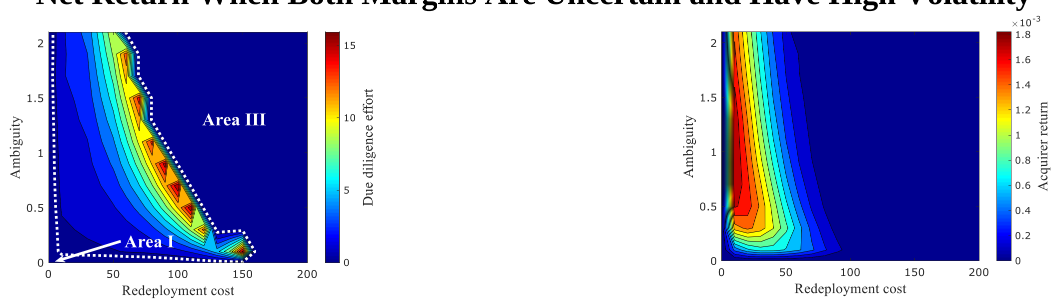
Implications of Sharing Factor and Ambiguity for Due Diligence Effort and Acquirer Net Return When Both Margins Are Uncertain and Have Low Volatility

Panel A. Optimal due diligence effort

Panel B. Acquirer net return with optimal due diligence effort

FIGURE B9

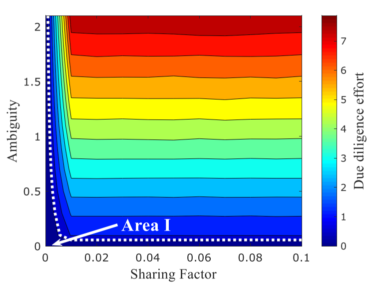
Implications of Redeployment Cost and Ambiguity for Due Diligence Effort and Acquirer Net Return When Both Margins Are Uncertain and Have High Volatility



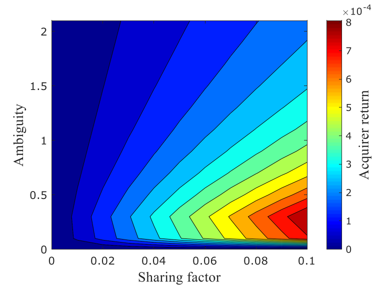
Panel A. Optimal due diligence effort

Panel B. Acquirer net return with optimal due diligence effort

FIGURE B10
Implications of Sharing Factor and Ambiguity for Due Diligence Effort and Acquirer Net Return When Both Margins Are Uncertain and Have High Volatility

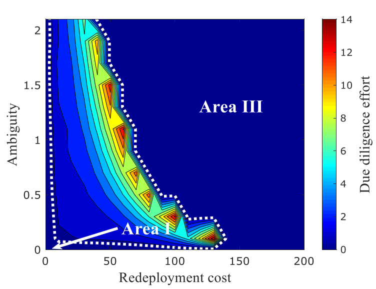


Panel A. Optimal due diligence effort

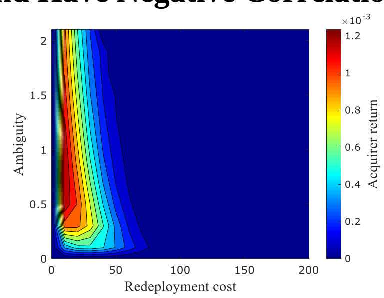


Panel B. Acquirer net return with optimal due diligence effort

FIGURE B11
Implications of Redeployment Cost and Ambiguity for Due Diligence Effort and Acquirer Net Return When Both Margins Are Uncertain and Have Negative Correlation

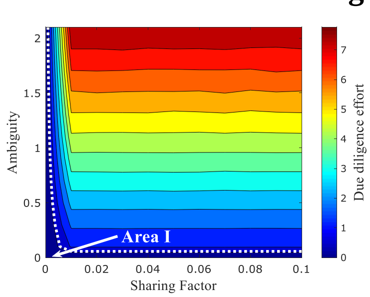


Panel A. Optimal due diligence effort

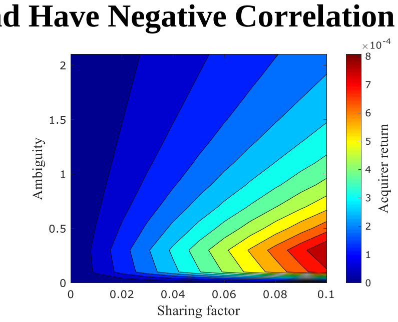


Panel B. Acquirer net return with optimal due diligence effort

FIGURE B12
Implications of Sharing Factor and Ambiguity for Due Diligence Effort and Acquirer Net Return When Both Margins Are Uncertain and Have Negative Correlation

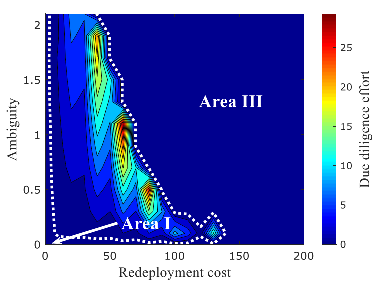


Panel A. Optimal due diligence effort

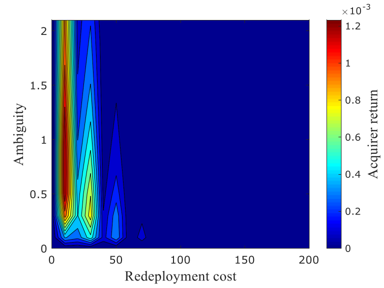


Panel B. Acquirer net return with optimal due diligence effort

FIGURE B13
Implications of Redeployment Cost and Ambiguity for Due Diligence Effort and Acquirer Net Return When Both Margins Are Uncertain and Have Positive Correlation

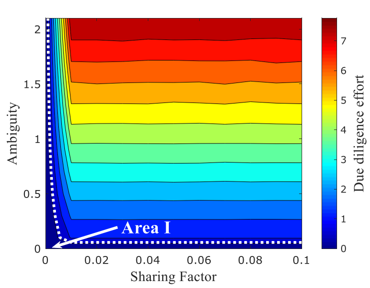


Panel A. Optimal due diligence effort

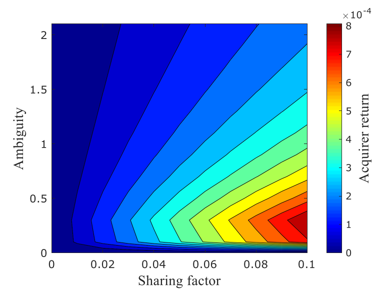


Panel B. Acquirer net return with optimal due diligence effort

FIGURE B14
Implications of Sharing Factor and Ambiguity for Due Diligence Effort and Acquirer Net Return When Both Margins Are Uncertain and Have Positive Correlation

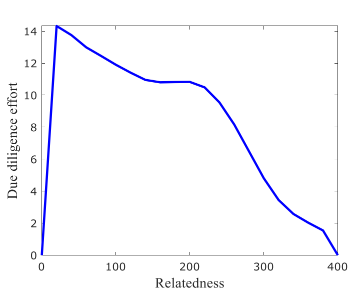


Panel A. Optimal due diligence effort

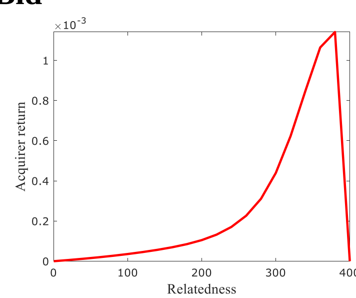


Panel B. Acquirer net return with optimal due diligence effort

FIGURE B15
Implications of Relatedness for Due Diligence Effort and Acquirer Net Return with Exogenous Alternative Bid



Panel A. Optimal due diligence effort



Panel B. Acquirer net return with optimal due diligence effort

FIGURE B16

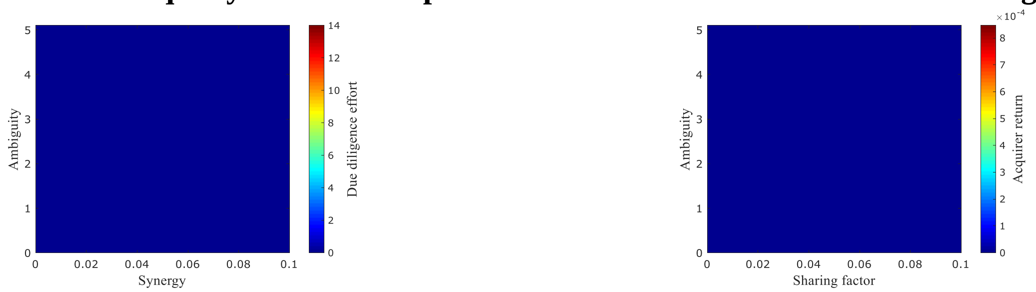
Implications of Redeployment Cost and Ambiguity for Due Diligence Effort and Acquirer Net Return When Equally- or More-Capable Alternative Bidder Conducts Due Diligence

Panel A. Optimal due diligence effort

Panel B. Acquirer net return with optimal due diligence effort

FIGURE B17

Implications of Sharing Factor and Ambiguity for Due Diligence Effort and Acquirer Net Return When Equally- or More-Capable Alternative Bidder Conducts Due Diligence

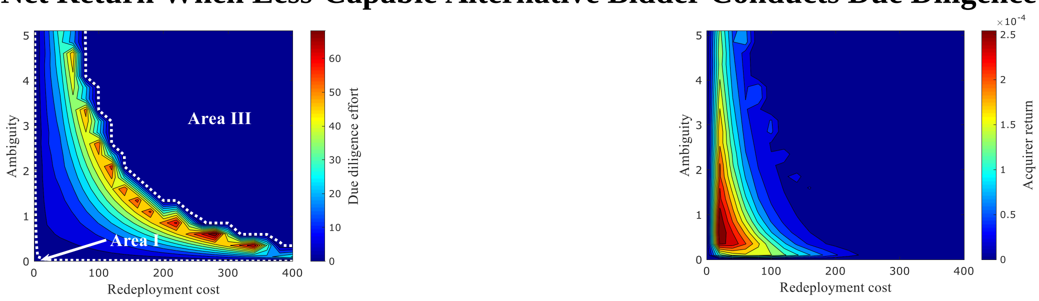


Panel A. Optimal due diligence effort

Panel B. Acquirer net return with optimal due diligence effort

FIGURE B18

Implications of Redeployment Cost and Ambiguity for Due Diligence Effort and Acquirer Net Return When Less-Capable Alternative Bidder Conducts Due Diligence



Panel A. Optimal due diligence effort

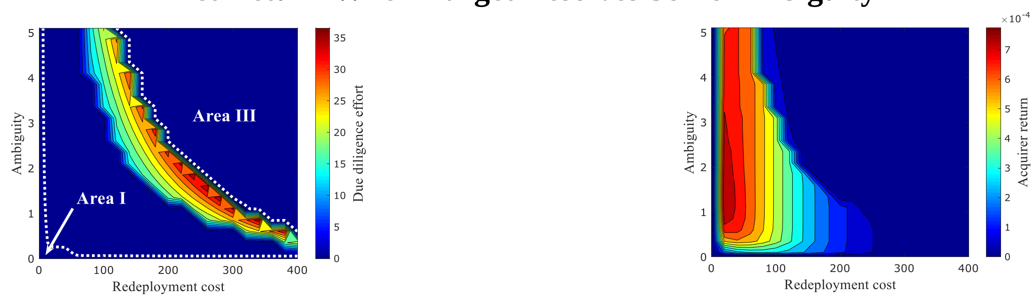
Panel B. Acquirer net return with optimal due diligence effort

FIGURE B19
Implications of Sharing Factor and Ambiguity for Due Diligence Effort and Acquirer Net Return When Less-Capable Alternative Bidder Conducts Due Diligence

Panel A. Optimal due diligence effort

Panel B. Acquirer net return with optimal due diligence effort

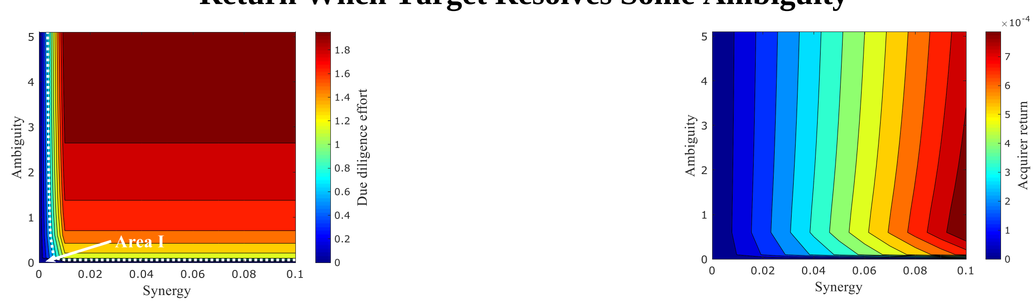
FIGURE B20
Implications of Redeployment Cost and Ambiguity for Due Diligence Effort and Acquirer Net Return When Target Resolves Some Ambiguity



Panel A. Optimal due diligence effort

Panel B. Acquirer net return with optimal due diligence effort

FIGURE B21
Implications of Sharing Factor and Ambiguity for Due Diligence Effort and Acquirer Net Return When Target Resolves Some Ambiguity



Panel A. Optimal due diligence effort

Panel B. Acquirer net return with optimal due diligence effort