Online Appendix

to accompany

Bid Anticipation, Information Revelation, and Merger Gains

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A Data

Table A.1: **Failed Bid Sample Construction**

This table summarizes the breakdown of the all failed bid sample into the endogenously failed bid sample and the exogenously failed bid sample. Failed bids whose reasons cannot be clearly identified are excluded.

Reasons that cannot be clearly classified		658
Endogenously failed bids	Target's refusal of the offer	125
	Acquirer loses to competing offers	106
	Big change in acquirer valuation during the bidding process	14
	Big change in target valuation during the bidding process	15
	Change in macro-economic conditions.	12
	Bad market reception/acquirer shareholder skepticism	8
	Acquirer cannot secure financing/financing too expensive	6
	Due diligence revelations about target	13
	Acquirer and target mutually agree to terminate a merger	29
	Hard to realize merger gains	6
Exogenously failed bids	Authority disapproval, litigation delay, environment concern, etc.	143
All failed bid sample		1,135

B Stationary Search Equilibrium

I define and solve the stationary search equilibrium in this subsection.

To simplify notation, I suppress the firm and time subscripts and use variables with a "prime" to denote the variable value next period. For example, $z' = z_{t+1}$. Under this recursive notation, the joint distribution $G(z, s)$ evolves according to the following dynamics:

$$G(z', s') = (1 - p_d) \int_z \int_s Q(z', s'; z, s) G(z, s) ds dz + \Upsilon(z', s') \tag{B.1}$$

where p_d is the exogenous exit rate of incumbents, and $\Upsilon(z, s)$ is the mass of entrants. p_d and $\Upsilon(z, s)$ don't drive the main model implications but are necessary to obtain a stationary search equilibrium. Given the joint distribution $G(z, s)$ and firm's optimal decision rule $\ell(z, s)$, the distribution of potential acquirers and targets can be easily derived as the conditional distribution

$$G_{Acq}(z,s) = P\left[(z,s)|\ell(z,s)=Acq\right] = \frac{G(z,s)\cdot I\left(\ell(z,s)=Acq\right)}{\int\limits_z\int\limits_s G(z,s)\cdot I\left(\ell(z,s)=Acq\right)dsdz} \tag{B.2}$$

$$G_{Tar}(z,s) = P\left[(z,s)|\ell(z,s)=Tar\right] = \frac{G(z,s)\cdot I\left(\ell(z,s)=Tar\right)}{\int\limits_z\int\limits_s G(z,s)\cdot I\left(\ell(z,s)=Tar\right)dsdz} \tag{B.3}$$

where $I(x)$ is the indicator function which equals to one if x is true and zero otherwise, and the value functions can be explicitly written as

$$V_{SA}(z,s) = \pi(z,s) + \beta\int\limits_{z'}\int\limits_{s'} V\left(z',s'\right)M(z',s';z,s)ds'dz' \tag{B.4}$$

$$V_{Acq}(z,s) = V_{SA}(z,s) + \beta\vartheta_A(1-\iota)\theta\int\limits_{\tilde{z}_T}\int\limits_{\tilde{s}_T}\left(\Sigma(z,s;\tilde{z}_T,\tilde{s}_T)\right)^+ G_{Tar}(\tilde{z}_T,\tilde{s}_T)d\tilde{s}_T d\tilde{z}_T - C \tag{B.5}$$

$$V_{Tar}(z,s) = V_{SA}(z,s) + \vartheta_T(1-\iota)\left(1-\theta\right)\int\limits_{\tilde{z}_A}\int\limits_{\tilde{s}_A}\left(\Sigma(\tilde{z}_A,\tilde{s}_A;z,s)\right)^+ G_{Acq}(\tilde{z}_A,\tilde{s}_A)d\tilde{s}_A d\tilde{z}_A - C \tag{B.6}$$

where the matching probability ϑ_A and ϑ_T are defined in Equation 8 and 9 of the main paper with $\Gamma_A = \int\limits_z\int\limits_s G(z,s)\cdot I\left(\ell(z,s)=Acq\right)dsdz$ and $\Gamma_T = \int\limits_z\int\limits_s G(z,s)\cdot I\left(\ell(z,s)=Tar\right)dsdz$, and $M(z',s';z,s)$ used in Equation B.4 measures the probability of transition from (z,s) to (z',s') driven only by the law of motion of z and s. Notice that $M(z',s';z,s)$ is different from $Q(z',s';z,s)$ that captures both the dynamics driven by the law of motion and the dynamics driven by the endogenous reallocation of seeds through M&A. We need to use $M(z',s';z,s)$ here to compute $V_{SA}(z,s)$, because we assume the firm stands alone this period, so no seed reallocation will happen to this firm and the evolution of its state variables is only driven by the law of motion that governs z and s.

Using the definitions of firm value functions, distribution of acquirers and targets, and the matching probability functions, we can define the stationary search equilibrium in the paper.

C Numerical Algorithm

I describe the numerical algorithm used for solving the stationary search equilibrium. I first transform the Equation 4 and 5 in the main paper into discrete-state Markov chains using the method in Tauchen (1986), letting both z and s have 10 points of support in $[\mu - \frac{4\sigma}{\sqrt{1-\rho^2}}, \mu + \frac{4\sigma}{\sqrt{1-\rho^2}}]$, where μ, σ and ρ are the corresponding mean, standard deviation and persistence parameters for these two AR(1) processes.

Given a set of parameters, I use an iterated fixed point algorithm to find the stationary search equilibrium:

1. Guess a candidate of the joint distribution of (z, s), that is, $G(z, s)$. I start with an initial guess of a uniform distribution;

2. Guess a candidate of firms' optimal decision $\ell(z, s)$. I start with an initial guess in which seed-constrained firms choose to be acquirers and seed-unconstrained firms choose to be targets;

3. Given $G(z, s)$ and $\ell(z, s)$, I compute the distribution of acquirers and targets (i.e., G_{Acq} and G_{Tar}) and their matching probabilities (i.e., ϑ_A and ϑ_T);

4. Use the fixed point algorithm to solve the value function V_{SA}, V_{Acq} and V_{Tar} and firms' optimal decision rule $\ell^{'}(z, s)$ from Equation B.4, B.5 and B.6;

5. Compare $\ell^{'}(z, s)$ with $\ell(z, s)$, stop if the difference is small enough; otherwise, replace $\ell(z, s)$ with $\ell^{'}(z, s)$ and repeat step 3 to 5 until convergence. Use the converged $\ell^{'}(z, s)$ as the updated optimal decision rule;

6. Use the updated optimal decision rule obtained in step 5, $\ell^{'}(z, s)$, to compute an updated transition matrix $Q^{'}$;

7. Iterate Equation B.1 using $\ell^{'}(z, s)$ and $Q^{'}$ until the joint distribution converges, and use this distribution as the updated joint distribution $G^{'}(z, s)$;

8. Compare $G^{'}(z, s)$ with $G(z, s)$, stop if the difference is small enough; otherwise, replace $G(z, s)$ with $G^{'}(z, s)$ and repeat step 2 to 8 until convergence.

9. A stationary search equilibrium is obtained when $G^{'}(z, s)$ converges to $G(z, s)$ and $\ell^{'}(z, s)$ converges to $\ell(z, s)$.

Though proving the existence of such a search equilibrium with ex-ante heterogeneous agents is possible (see e.g., Lu and McAfee (1996)), it is challenging (e.g., Shimer and Smith (2000) and Shimer and Smith (2001)) and would necessitate a protracted detour from the main focus of my analysis. So I limit my analysis to the equilibrium solutions found by the numerical algorithm. Though I don't provide a rigorous proof of the existence of such an equilibrium in this paper, the numerical solution shows that for a wide range of parameters that are empirically relevant, the equilibrium always exists.

D Firms' Market Values

D.1 Before takeover announcements

At stage 0 in Figure 1 of the main paper, firms make their optimal takeover decisions based on their state variables realized at the beginning of this period t. For an acquirer candidate with state variables $(z_{i,t}, s_{i,t})$, its *true* value at this stage is solved as:

$$V_{Acq}^{(0)}(z_{i,t}, s_{i,t}) = V_{SA}(z_{i,t}, s_{i,t}) + \beta\vartheta_A(1-\iota)\theta E\left[(\Sigma(z_{i,t}, s_{i,t}; \tilde{z}_{T,t}, \tilde{s}_{T,t}))^+\right] - C$$

Similarly, a target candidate with state variables $(z_{i,t}, s_{i,t})$ has the *true* value:

$$V_{Tar}^{(0)}(z_{i,t}, s_{i,t}) = V_{SA}(z_{i,t}, s_{i,t}) + \beta\vartheta_T(1-\iota)(1-\theta) E\left[(\Sigma(\tilde{z}_{A,t}, \tilde{s}_{A,t}; z_{i,t}, s_{i,t}))^+\right] - C$$

and a stand-alone firm with state variables $(z_{i,t}, s_{i,t})$ has the *true* value:

$$V_{SA}^{(0)}(z_{i,t}, s_{i,t}) = \pi(z_{i,t}, s_{i,t}) + \beta E\left[V\left(z_{i,t+1}, s_{i,t+1}\right)\right]$$

I assume the market does not observe the firm's contemporaneous state variables. That is, for any firm i at period t, the market does not know $(z_{i,t}, s_{i,t})$. Instead, at the beginning of each period t, the market receives firm i's financial statement regarding its performance in the *last* period $t-1$. From the financial statement, the market learns firm i's productivity in period $t-1$, $z_{i,t-1}$, and the physical capital employed in period $t-1$, $K_{i,t-1}$. But the market does not directly observe firm$i$'s stock of seed, $s_{i,t-1}$. That is:

$$\mathcal{F}_t^{(0)} = \{z_{i,t-1}, K_{i,t-1}\}$$

The market conjectures the distribution of $(z_{i,t-1}, s_{i,t-1})$ based on $\mathcal{F}^{(0)}$ as follows: $z_{i,t-1}$ is directly observed in $\mathcal{F}^{(0)}$. For $s_{i,t-1}$, if firm i was operating below its optimal capacity defined in Equation 2 of the main paper (i.e., $K_{i,t-1} < K_{i,t-1}^*$) at $t-1$, the market understands that firm i was seed constrained (i.e., $s_{i,t-1} < ln(K_{i,t-1}^*)$) and therefore its stock of seeds exactly equals the observed capital, that is, $s_{i,t-1} = ln(S_{i,t-1}) = ln(K_{i,t-1})$. In this case, firm i's seeds at period $t-1$ are revealed to the market.

On the other hand, if firm i was operating at its optimal capacity $K_{i,t-1}^*$, the market understands that firm i is not seed constrained, so $s_{i,t-1} \geq ln(K_{i,t-1}^*)$. But in this case, the market does not know the exact value of $s_{i,t-1}$. Market then uses the joint distribution $G(z, s)$ in equilibrium and the observed productivity $z_{i,t-1}$ to conjectures the distribution of $s_{i,t-1}$ as follows:

$$P\left(s|s \geq ln(K^*_{i,t-1}); z_{i,t-1}\right) \;=\; \frac{G(z_{i,t-1}, s) \cdot I\left(s \geq ln(K^*_{i,t-1})\right)}{\int_s G(z_{i,t-1}, s) \cdot I\left(s \geq ln(K^*_{i,t-1})\right) ds}$$

where $I(x)$ is the indicator function which equals one if x is true and zero otherwise, and $K^*_{i,t-1}$ is defined in Equation 2 of the main paper. Figure 2c in the paper summarizes the market's information set. For firms locating in the shadow area in period $t-1$, the market cannot perfectly know their stock of seeds $s_{i,t-1}$ and considers $s_{i,t-1}$ to be a random variable following the distribution specified in the equation above; for firms locating outside the shadow area in period $t-1$, the market perfectly knows their stock of seeds $s_{i,t-1} = ln(K_{i,t-1})$.

At stage 0, before any takeover announcements are made public, the market does not know firms' optimal takeover decisions, and it cannot distinguish acquirers and targets from stand-alone firms. So it prices firm i at this stage as:

$$\begin{aligned} MV^{(0)}_{i,t} &= E\left[max\left\{V^{(0)}_{SA}(z_{i,t}, s_{i,t}), V^{(0)}_{Acq}(z_{i,t}, s_{i,t}), V^{(0)}_{Tar}(z_{i,t}, s_{i,t})\right\}|\mathcal{F}^{(0)}_t\right] \\ &= E\left[E\left[max\left\{V^{(0)}_{SA}(z_{i,t}, s_{i,t}), V^{(0)}_{Acq}(z_{i,t}, s_{i,t}), V^{(0)}_{Tar}(z_{i,t}, s_{i,t})\right\}|(z_{i,t-1}, s_{i,t-1})\right]|\mathcal{F}^{(0)}_t\right] \end{aligned} \tag{D.1}$$

where the first equality holds by the definition of market value and the second equality holds by the law of iterated expectations. The law of iterated expectations explains how the market evaluates a firm: the market first conjectures the distribution of the firm's state variables at period $t-1$, that is $(z_{i,t-1}, s_{i,t-1})$, based on the market's information set at this stage $\mathcal{F}^{(0)}_t$ as I described above; then the firm's market value is computed as the weighted average of its true values, weighted by the transition probability from a given state $(z_{i,t-1}, s_{i,t-1})$ to a possible state $(z_{i,t}, s_{i,t})$.

D.2 No takeover announcement

If a firm makes no bid announcement, it reaches stage 1 of Figure 1 in the main paper. The event of no bid announcement delivers several new pieces of information to the market regarding the firm. First, the market now knows that the firm will stand alone in this period; second, the market updates its information set to incorporate the fact that no bid announcement is made by the firm:

$$\mathcal{F}^{(1)}_t = \mathcal{F}^{(0)}_t \cup \{No\ Bid\}$$

So the market value of the firm changes from $MV^{(0)}_{i,t}$ in equation D.1 to

$$MV^{(1)}_{i,t} = E\left[V_{SA}(z_{i,t}, s_{i,t})|\mathcal{F}^{(1)}_t\right] - C \cdot \left(P\left(\ell_{i,t} = Acq|\mathcal{F}^{(1)}_t\right) + P\left(\ell_{i,t} = Tar|\mathcal{F}^{(1)}_t\right)\right) \tag{D.2}$$

where ℓ is firms' optimal takeover decision rule and $1(\cdot)$ is the indicator function. It is worth noting that the event of no bid announcement does not necessarily imply that the firm chose to stand alone at stage 0. It is possible that the firm chose to become an acquirer or target at stage 0 but just failed to match with a partner during the random matching process. The searching process is unobservable, so the market cannot tell exactly why the firm stands alone. As a result, an expected search cost is deducted from the firm's stand-alone value in equation D.2.

Using the iterated expectation formula, we can rewrite the two components in D.2 as

$$\begin{aligned} E\left[V_{SA}(z_{i,t},s_{i,t})|\mathcal{F}_t^{(1)}\right] &= E\left[V_{SA}(z_{i,t},s_{i,t})|\ell_{i,t}=SA,\mathcal{F}_t^{(1)}\right]\cdot P\left(\ell_{i,t}=SA|\mathcal{F}_t^{(1)}\right) \\ &\quad + E\left[V_{SA}(z_{i,t},s_{i,t})|\ell_{i,t}=Acq,\mathcal{F}_t^{(1)}\right]\cdot P\left(\ell_{i,t}=Acq|\mathcal{F}_t^{(1)}\right) \\ &\quad + E\left[V_{SA}(z_{i,t},s_{i,t})|\ell_{i,t}=Tar,\mathcal{F}_t^{(1)}\right]\cdot P\left(\ell_{i,t}=Tar|\mathcal{F}_t^{(1)}\right) \end{aligned}$$

The conditional probabilities in the equations above can be derived as follows:

$$P\left(\ell_{i,t}=SA|\mathcal{F}_t^{(1)}\right) = \frac{P\left(\ell_{i,t}=SA|\mathcal{F}_t^{(0)}\right)}{P\left(\ell_{i,t}=SA|\mathcal{F}_t^{(0)}\right)+(1-\vartheta_A)P\left(\ell_{i,t}=Acq|\mathcal{F}_t^{(0)}\right)+(1-\vartheta_T)P\left(\ell_{i,t}=Tar|\mathcal{F}_t^{(0)}\right)}$$

$$P\left(\ell_{i,t}=Acq|\mathcal{F}_t^{(1)}\right) = \frac{(1-\vartheta_A)P\left(\ell_{i,t}=Acq|\mathcal{F}_t^{(0)}\right)}{P\left(\ell_{i,t}=SA|\mathcal{F}_t^{(0)}\right)+(1-\vartheta_A)P\left(\ell_{i,t}=Acq|\mathcal{F}_t^{(0)}\right)+(1-\vartheta_T)P\left(\ell_{i,t}=Tar|\mathcal{F}_t^{(0)}\right)}$$

$$P\left(\ell_{i,t}=Tar|\mathcal{F}_t^{(1)}\right) = \frac{(1-\vartheta_T)P\left(\ell_{i,t}=Tar|\mathcal{F}_t^{(0)}\right)}{P\left(\ell_{i,t}=SA|\mathcal{F}_t^{(0)}\right)+(1-\vartheta_A)P\left(\ell_{i,t}=Acq|\mathcal{F}_t^{(0)}\right)+(1-\vartheta_T)P\left(\ell_{i,t}=Tar|\mathcal{F}_t^{(0)}\right)}$$

where $1-\vartheta_A$ and $1-\vartheta_T$ capture the probability of no matching (therefore no bid announcement) for an acquirer or target, respectively.

D.3 After takeover announcements

At stage 2 of Figure 1 in the paper, acquirers and targets that are successfully matched make takeover announcements. For an acquirer with state variables $(z_{i,t},s_{i,t})$, let's assume it meets with a target with state variables $(z_{j,t},s_{j,t})$, and its *true* value at this stage is:

$$V_{Acq}^{(2)}(z_{i,t},s_{i,t}) = V_{SA}(z_{i,t},s_{i,t}) + \beta(1-\iota)\theta\left(\Sigma(z_{i,t},s_{i,t};z_{j,t},s_{j,t})\right)^+ - C$$

Comparing $V_{Acq}^{(2)}(z_{i,t},s_{i,t})$ with $V_{Acq}^{(0)}(z_{i,t},s_{i,t})$, we notice two important differences. First, the matching probability ϑ_A drops out from the equation of $V_{Acq}^{(2)}(z_{i,t},s_{i,t})$ since the random matching already happened at stage 2. Second, the synergy gain in $V_{Acq}^{(2)}(z_{i,t},s_{i,t})$ is now $(\Sigma(z_{i,t},s_{i,t};z_{j,t},s_{j,t}))^+$ rather than $E\left[(\Sigma(z_{i,t},s_{i,t};\tilde{z}_{T,t},\tilde{s}_{T,t}))^+\right]$, because the target is identified after random matching.

Similarly, the target's *true* value at this stage is:

$$V_{Tar}^{(2)}(z_{j,t},s_{j,t}) = V_{SA}(z_{j,t},s_{j,t}) + \beta(1-\iota)(1-\theta)\left(\Sigma(z_{i,t},s_{i,t};z_{j,t},s_{j,t})\right)^+ - C$$

At stage 2, the market observes the takeover announcements and knows the identities of acquirers and targets as well as the offer price. The market now knows that $\ell_{i,t} = Acq$ and $\ell_{j,t} = Tar$, where ℓ is firms' optimal takeover decision rule. The market also knows the offer price $P_{i,j,t}$ which is informative of the two involving firms' state variables. Because the market does not observe firms' state variables directly, the observed takeover decisions and offer price provide new information to the market regarding the firms' state variables. As a result, the market's information set at stage 2 is expanded to:

$$\mathcal{F}_t^{(2)} = \mathcal{F}_t^{(0)} \cup \left\{\ell_{i,t} = Acq, \ell_{j,t} = Tar,\ P_{i,j,t}\right\}$$

The acquirer's market value and the target's market value at this stage are then defined as the expectation of their true values, conditioning on the market's information set:

$$MV_{Acq,t}^{(2)} = E\left[V_{SA}(z_{i,t}, s_{i,t})|\mathcal{F}_t^{(2)}\right] + \beta(1-\iota)\theta E\left[\left(\Sigma(z_{i,t}, s_{i,t}; z_{j,t}, s_{j,t})\right)^+ |\mathcal{F}_t^{(2)}\right] - C \quad \text{(D.3)}$$

$$MV_{Tar,t}^{(2)} = E\left[V_{SA}(z_{j,t}, s_{j,t})|\mathcal{F}_t^{(2)}\right] + \beta(1-\iota)(1-\theta) E\left[\left(\Sigma(z_{i,t}, s_{i,t}; z_{j,t}, s_{j,t})\right)^+ |\mathcal{F}_t^{(2)}\right] - C \quad \text{(D.4)}$$

The expectation can be computed using the conditional expectation formula and the Bayesian rule given that $\ell_{i,t}$, $\ell_{j,t}$, and $P_{i,j,t}$ are all functions of firm state variables.

D.4 After exogenous bid terminations

After takeover announcements, the proposed bids are subjected to exogenous challenges. If a proposed bid is called off exogenously at stage 3 of Figure 1, the acquirer and target lose their expected merger gains from this bid and their *true* values drop to:

$$\begin{aligned} V_{Acq}^{(3)}(z_{i,t}, s_{i,t}) &= V_{SA}(z_{i,t}, s_{i,t}) - C \\ V_{Tar}^{(3)}(z_{j,t}, s_{j,t}) &= V_{SA}(z_{j,t}, s_{j,t}) - C \end{aligned}$$

Notice that the search cost is a sunk cost, so it is subtracted from the firm value despite the outcome. Since the bid is called off exogenously, no new information regarding the firm's state variables are revealed to the market and hence the market possesses the same information set as it does at stage 2:

$$\mathcal{F}_t^{(3)} = \mathcal{F}_t^{(2)}$$

and the market values are:

$$MV_{Acq,t}^{(3)} = E\left[V_{SA}(z_{i,t}, s_{i,t})|\mathcal{F}_t^{(3)}\right] - C \quad \text{(D.5)}$$

$$MV_{Tar,t}^{(3)} = E\left[V_{SA}(z_{j,t}, s_{j,t})|\mathcal{F}_t^{(3)}\right] - C \quad \text{(D.6)}$$

D.5 After merger completion

If a merger is completed at stage 4 of Figure 1, the acquirer and target get their own share of merger gains:

$$\begin{aligned} V_{Acq}^{(4)}(z_{i,t}, s_{i,t}) &= V_{SA}(z_{i,t}, s_{i,t}) + \theta \left(\Sigma(z_{i,t}, s_{i,t}; z_{j,t}, s_{j,t})\right)^{+} - C \\ V_{Tar}^{(4)}(z_{i,t}, s_{i,t}) &= V_{SA}(z_{i,t}, s_{i,t}) + (1-\theta) \left(\Sigma(z_{i,t}, s_{i,t}; z_{j,t}, s_{j,t})\right)^{+} - C \end{aligned}$$

Denote the market's reception of new information from the completed merger between acquirer i and target j as $\mathcal{O}_{i,j,t} = Suc$, and the market's information set at stage 4 is:

$$\mathcal{F}_t^{(4)} = \mathcal{F}_t^{(2)} \cup \{\mathcal{O}_{i,j,t} = Suc\}$$

The acquirer's market value and the target's market value at this stage are:

$$MV_{Acq,t}^{(4)} = E\left[V_{SA}(z_{i,t}, s_{i,t}) | \mathcal{F}_t^{(4)}\right] + \theta E\left[\left(\Sigma(z_{i,t}, s_{i,t}; z_{j,t}, s_{j,t})\right)^{+} | \mathcal{F}_t^{(4)}\right] - C \tag{D.7}$$

$$MV_{Tar,t}^{(4)} = E\left[V_{SA}(z_{j,t}, s_{j,t}) | \mathcal{F}_t^{(4)}\right] + (1-\theta) E\left[\left(\Sigma(z_{i,t}, s_{i,t}; z_{j,t}, s_{j,t})\right)^{+} | \mathcal{F}_t^{(4)}\right] - C \tag{D.8}$$

D.6 After endogenous bid terminations

If a merger fails to consummate endogenously at stage 5 of Figure 1, the acquirer and target lose their expected merger gains from this bid and their *true* values drop to:

$$\begin{aligned} V_{Acq}^{(5)}(z_{i,t}, s_{i,t}) &= V_{SA}(z_{i,t}, s_{i,t}) - C \\ V_{Tar}^{(5)}(z_{j,t}, s_{j,t}) &= V_{SA}(z_{j,t}, s_{j,t}) - C \end{aligned}$$

Endogenous deal failure reveals new information to the market regarding the acquirer and target. Denote the market's reception of endogenous deal failure between acquirer i and target j as $\mathcal{O}_{i,j,t} = Fail$, and the market's information set at stage 5 is:

$$\mathcal{F}_t^{(5)} = \mathcal{F}_t^{(2)} \cup \{\mathcal{O}_{i,j,t} = Fail\}$$

The acquirer's market value and the target's market value at this stage are:

$$MV_{Acq,t}^{(5)} = E\left[V_{SA}(z_{i,t}, s_{i,t}) | \mathcal{F}_t^{(5)}\right] - C \tag{D.9}$$

$$MV_{Tar,t}^{(5)} = E\left[V_{SA}(z_{j,t}, s_{j,t}) | \mathcal{F}_t^{(5)}\right] - C \tag{D.10}$$

It is worth noting that, for a given acquirer or target, its *true* value falls to the same level after bid termination, no matter the bid is canceled endogenously or exogenously. That is, $V_{Acq}^{(3)}(z_{i,t}, s_{i,t}) = V_{Acq}^{(5)}(z_{i,t}, s_{i,t})$ and $V_{Tar}^{(3)}(z_{i,t}, s_{i,t}) = V_{Tar}^{(5)}(z_{i,t}, s_{i,t})$. However, the firm's market value differs after different types of bid terminations. This is because, exogenous bid failure reveals no new information regarding the firm while endogenous bid failure is informative of the involving firms' state variables.

E Decomposition of the Revelation Effect

To decompose the revelation effect, I start with its definition provided in Equation 24 of the main paper, which I reproduce below. For acquirer i, its revelation effect is:

$$Revelation = E\left[V_{SA}(z_{i,t}, s_{i,t})|\mathcal{F}_t^{(2)}\right] - E\left[V_{SA}(z_{i,t}, s_{i,t})|\mathcal{F}_t^{(0)}\right]$$

Before the bid announcement, the market does not know firm i is an acquirer, and it perceives a distribution of firm i's state variables based on its information set $\mathcal{F}_t^{(0)}$. Let's denote this pre-announcement distribution as μ_0, and μ_0 is used to compute the expectation $E\left[V_{SA}(z_{i,t}, s_{i,t})|\mathcal{F}_t^{(0)}\right]$. After the bid announcement, the market realizes that firm i is an acquirer and thus its state variables must belong to the acquirer set. The market updates its perceived distribution based on $\mathcal{F}_t^{(2)}$ and let's denote this post-announcement distribution as μ_2, and μ_2 is used to compute the expectation $E\left[V_{SA}(z_{i,t}, s_{i,t})|\mathcal{F}_t^{(2)}\right]$. Using μ_0 and μ_2, we can rewrite the revelation effect as:

$$Revelation = \iint V_{SA}(z_{i,t}, s_{i,t})\mu_2 dzds - \iint V_{SA}(z_{i,t}, s_{i,t})\mu_0 dzds$$

To evaluate how much revelation effect is driven by shocks to s, I assume that the market preserves the pre-announcement distribution of z (conditioning on s) and only updates the marginal distribution of s upon observing the bid announcement. This partial update results in a distribution f_{z_0,s_2}, whose subscripts imply that the conditional distribution of z is identical to the pre-announcement distribution and the distribution of s is updated. The intuition of f_{z_0,s_2} is that it assumes the market only perceives shocks to s and ignores shocks to z.

The revelation effect induced by shocks to s is defined as

$$s\_Rev = \iint V_{SA}(z_{i,t}, s_{i,t})f_{z_0,s_2} dzds - \iint V_{SA}(z_{i,t}, s_{i,t})\mu_0 dzds$$

Similarly, we can define a partial update of the distribution f_{z_2,s_0} in which the pre-announcement distribution of s (conditioning on any value of z) is preserved and only the marginal distribution of z is updated, and it assumes the market only perceives shocks to z and ignores shocks to s. The revelation effect induced by shocks to z is therefore:

$$z\_Rev = \iint V_{SA}(z_{i,t}, s_{i,t})f_{z_2,s_0} dzds - \iint V_{SA}(z_{i,t}, s_{i,t})\mu_0 dzds$$

It is worth noting that the sum of s_Rev and z_Rev is not necessarily equal to the total revelation effect *Revelation*, because the value function $V_{SA}(z_{i,t}, s_{i,t})$ is not linear in z and s and a full update of the distribution (i.e., from μ_0 to μ_2) may incorporate some correlation in

z and s. Therefore, I decompose the revelation effect as follows:

$$Revelation = s\_Rev + z\_Rev + zs\_Rev$$

where zs_Rev captures the cross effect of z and s.

The revelation effect of target firms can be decomposed analogously. After decomposing the revelation effect for each firm in the model economy, I perform the variance decomposition as follows:

$$Var(Revaltion) = Var(s\_Rev) + Var(z\_Rev) + Cov(z, s)$$

where $Cov(z, s)$ captures the term $Var(zs\_Rev)$ and the total covariance among s_Rev, z_Rev, and zs_Rev.

Below, I derive the partial update of distribution f_{z_0,s_2} and f_{z_2,s_0} and give a numerical example demonstrating how to decompose the revelation effect. Denote the pre-announcement distribution of z conditioning on s as $\mu_0^{z|s}$, which can be derived as:

$$\mu_0^{z|s} = \frac{\mu_0(z, s)}{\int \mu_0(z, s)dz}$$

Denote the marginal distribution of s post-announcement as μ_2^s:

$$\mu_2^s = \int \mu_2(z, s)dz$$

The partial update of distribution f_{z_0,s_2} is equal to

$$f_{z_0,s_2} = \mu_0^{z|s} \cdot \mu_2^s = \frac{\int \mu_2(z, s)dz}{\int \mu_0(z, s)dz} \cdot \mu_0(z, s)$$

Similarly, the partial update of distribution f_{z_2,s_0} is

$$f_{z_2,s_0} = \mu_0^{s|z} \cdot \mu_2^z = \frac{\int \mu_2(z, s)ds}{\int \mu_0(z, s)ds} \cdot \mu_0(z, s)$$

A simple numerical example follows. Let's assume that both z and s can take three possible values in this example, low (L), middle (M), or high (H). We can then characterize a firm's state variables in a 3-by-3 matrix, with s on the row and z on the column. I arrange s and z in such an order that the southeast part of the matrix represents firms that are constrained in s and the northwest part represents firms that are constrained in z, which are consistent with the convention used in Figure 2.

$$\begin{array}{cc} & z \\ s & \begin{bmatrix} H,L & H,M & H,H \\ M,L & M,M & M,H \\ L,L & L,M & L,H \end{bmatrix} \end{array}$$

Assume the market observes that a firm's *previous* state variables are (M, M), and the transition probabilities are given as below:

$$P(z = H|z = M) = P(z = L|z = M) = 0.1,\ P(z = M|z = M) = 0.8$$

$$P(s = H|s = M) = P(s = L|s = M) = 0.2,\ P(s = M|s = M) = 0.6$$

So in this example, z is more persistent than s. Since z and s are independent, in the pre-announcement period, the market perceived distribution of the firm's *current* state variables is

$$\mu_0 = \begin{bmatrix} 0.02, & 0.16, & 0.02 \\ 0.06, & 0.48, & 0.06 \\ 0.02, & 0.16, & 0.02 \end{bmatrix}$$

Let's assume that firms with state variables (M, H), (L, H), and (L, M) are acquirers, so upon observing the takeover announcement, the market updates its perceived distribution to

$$\mu_2 = \begin{bmatrix} 0, & 0, & 0 \\ 0, & 0, & 0.250 \\ 0, & 0.667, & 0.083 \end{bmatrix}$$

μ_2 reassigns the probability mass conditioning on the fact that an acquiring firm must locates in the southeast part of the matrix. So if the firm's state variables were (M, M) in the last period, upon observing it making a takeover announcement, the market perceives that there is a chance of 66.7% that the firm receives a negative shock to s and moves to the state of (L, M) this period, a chance of 25% that it receives a positive shock to z and moves to (M, H), and a chance of 8.3% that it receives both shocks and moves to (L, H).

Let's also specify V_{SA} for each state as follows:

$$V_{SA} = \begin{bmatrix} 1.2, & 1.7, & 2.0 \\ 0.8, & 1.4, & 1.7 \\ 0, & 0.8, & 1.4 \end{bmatrix}$$

So the value function is normalized to zero for firms constrained in both dimensions (i.e.,

(L,L)). Now the total revelation effect is equal to

$$\begin{aligned} Revelation &= E\left[V_{SA}|\mu_2\right] - E\left[V_{SA}|\mu_0\right] \\ &= -0.24 \end{aligned}$$

The partial update of distribution, f_{z_0,s_2} and f_{z_2,s_0} are

$$f_{z_0,s_2} = \begin{bmatrix} 0, & 0, & 0 \\ 0.025, & 0.200, & 0.025 \\ 0.075 & 0.600, & 0.075 \end{bmatrix}, \qquad f_{z_2,s_0} = \begin{bmatrix} 0, & 0.133, & 0.067 \\ 0, & 0.400, & 0.200 \\ 0, & 0.133, & 0.067 \end{bmatrix}$$

The first row (i.e., $s = H$) is updated to zero in f_{z_0,s_2} because when s is updated, the market knows that the acquirer cannot have $s = H$. Meanwhile, since z is not updated in f_{z_0,s_2}, the states associated with $z = L$ (i.e., the first column) still carry some probability. Similarly, in f_{z_2,s_0}, the first column (i.e., $z = L$) is updated to zero but the states associated with $s = H$ (i.e., the first row) still carry some probability, because only z is updated and s is not updated. As a result,

$$\begin{aligned} s\_Rev &= E\left[V_{SA}|f_{z_0,s_2}\right] - E\left[V_{SA}|\mu_0\right] \\ &= -0.387 \\ z\_Rev &= E\left[V_{SA}|f_{z_2,s_0}\right] - E\left[V_{SA}|\mu_0\right] \\ &= 0.145 \end{aligned}$$

which implies that the cross effect is:

$$\begin{aligned} zs\_Rev &= Revelation - s\_Rev - z\_Rev \\ &= 0.002 \end{aligned}$$

In this example, s_Rev is more than two times as large as z_Rev in magnitude. This is because s is less persistent than z (so the market perceives that the acquisition decision is more likely driven by shocks to s), and shocks to s have a larger effect on firm value (i.e., $V_{SA}(3,2) - V_{SA}(2,2) = 0.8 - 1.4 = -0.6$) than shocks to z (i.e., $V_{SA}(2,3) - V_{SA}(2,2) = 1.7 - 1.4 = 0.3$).

F Constructing the Covariance Matrix

I follow Taylor (2010) in constructing the covariance matrix and the efficient weighting matrix using the seemingly unrelated regressions approach. Specifically, I express moments as the coefficients from a system of regression equations, each of which takes the form

$$Y_i = X_i \beta_i + e_i$$

in which X, Y, and e are vectors and the subscript i indicates the equation. Y_i is $N_i \times 1$ and β_i is $k_i \times 1$. The covariance between moments estimators β_i and β_j is

$$Cov(\beta_i, \beta_j) = (X_i^{'} X_i)^{-1} X_i^{'} \Omega_{ij} X_j (X_j^{'} X_j)^{-1}$$

where $\Omega_{ij} = Cov(e_i, e_j)$ is the $N_i \times N_j$ matrix whose element t and s is $Cov(e_{it}, e_{js})$. To allow for serial correlation and cross-sectional correlation, I assume that observations involving firms in the same Fama-French 48 industry and events within a [-1,1] year window are possibly correlated. I estimate the covariance matrix Ω_{ij} for each pair of moments i, j.

Define

$$G_N = M_N - \frac{1}{L} \sum_{l=1}^{L} m_n^l(\theta)$$

and we obtain

$$\sqrt{N}\left(\hat{\theta} - \theta_0\right) \rightarrow^d \mathbb{N}(0, \Sigma)$$
$$\Sigma = \left(1 + \frac{1}{L}\right)\left(\Gamma' \Lambda^{-1} \Gamma\right)^{-1}$$

where L is the number of simulated data sets which I choose as 20, $\Gamma = \partial \hat{G}(\theta_0)/\partial \theta'$ is computed as numerical differentiation of G_N at the parameter point estimates, and $\Lambda = Navar\left(\hat{M}(\theta_0)\right)$ is N times the covariance matrix of empirical moments.

G Hubris Motives and Agency Costs

I extend the baseline model to incorporate the hubris motive of M&As. I assume that in the extended model, firms still make their optimal decisions of M&As as in the baseline model. Meanwhile, firms with state variable $(z_t, s_t) \geq (\bar{z} + m\sigma_z, \bar{s} + m\sigma_s)$ have a probability η to acquire another firm due to managerial hubris. I assume that both types of acquirers go through the same merger process as described in Figure 1 of the paper.

If a firm wakes up at time t and finds itself in the regime of hubristic acquirers (i.e., $(z_t, s_t) \geq (\bar{z} + m\sigma_z, \bar{s} + m\sigma_s)$), it has a probability η to pursue an acquisition due to managerial hubris. If it does so, it has a probability ϑ_A to match with a target firm:

$$\vartheta_A = \lambda max\{\frac{\Gamma_T}{\Gamma_A^{hbr} + \Gamma_A^{syn}}, 1\} \tag{G.1}$$

where Γ_T is the population of targets, and Γ_A^{hbr} (Γ_A^{syn}) is the population of hubristic (synergistic) acquirers. Equation G.1 assumes that both hubristic acquirers and synergistic acquirers compete for the same set of targets, and $\Gamma_A^{hbr} + \Gamma_A^{syn}$ captures the population of all acquirers. If a hubristic acquirer meets with a target in the random matching process, a bid announcement is made and the hubristic bid is subject to the exogenous challenges as synergistic bids do. I retain this assumption for two reasons. First, in reality, both hubristic acquisitions and synergistic acquisitions may fail for exogenous reasons. Second, I will construct new data moments from the exogenously failed bid sample that are informative in identifying hubristic acquisitions, so creating their model counterparts is necessary.

If a hubristic bid survives the exogenous challenge, the acquirer and the target need to decide whether to complete the deal. Clearly, hubristic acquisitions often destroy value in the extended model, but I assume that they go through because of the strong managerial hubris. This assumption implies that hubristic acquisitions never fail endogenously: Endogenous bid failure occurs in the baseline model when a proposed merger generates low or even negative synergistic values. Apparently, if we allow endogenous bid failure in hubristic acquisitions, then most hubristic acquisitions would fail endogenously. In other words, hubristic acquisitions happen in the model precisely because managerial hubris prevents endogenous bid failure from taking place.

For a hubristic acquisition to consummate, the acquirer and target also need to agree on an offer price. I assume that the acquirer pays the target a premium γ which follows a normal distribution with mean μ_γ and standard deviation σ_γ.

Though the hubristic acquirers' M&A decisions are exogenously specified in the extended model, the synergistic acquirers and the targets still make endogenous M&A decisions to maximize their values. Due to the presence of hubristic acquirers in the extended model, their Bellman equations differ from Equations 14 to 16 in the main paper:

$$\begin{aligned}
V_{SA}(z_{i,t}, s_{i,t}) &= \pi(z_{i,t}, s_{i,t}) + \beta E\left[V\left(z_{i,t+1}, s_{i,t+1}\right)\right] && \text{(G.2)}\\
V_{Acq}^{syn}(z_{i,t}, s_{i,t}) &= V_{SA}(z_{i,t}, s_{i,t}) + \beta\vartheta_A(1-\iota)\theta E\left[\left(\Sigma(z_{i,t}, s_{i,t}; \tilde{z}_{T,t}, \tilde{s}_{T,t})\right)^+\right] - C && \text{(G.3)}\\
V_{Tar}(z_{i,t}, s_{i,t}) &= V_{SA}(z_{i,t}, s_{i,t}) + \beta\vartheta_T^{syn}(1-\iota)(1-\theta)\, E\left[\left(\Sigma(\tilde{z}_{A,t}, \tilde{s}_{A,t}; z_{i,t}, s_{i,t})\right)^+\right] \\
&\quad + \beta\vartheta_T^{hbr}(1-\iota)E[\gamma]\, V_{SA}(z_{i,t}, s_{i,t}) - C && \text{(G.4)}
\end{aligned}$$

For synergistic acquirers, their matching probability ϑ_A is now determined by equation G.1. This is because the matching is random and each individual acquirer, regardless of its type, has the same probability of meeting with a target. The matching probability is reduced because of the competition from hubristic acquirers. For targets, they may match with synergistic acquirers or hubristic acquirers and the matching probability, ϑ_T^{syn} and ϑ_T^{hbr}, are defined below:

$$\vartheta_T^{syn} = \lambda max\{\frac{\Gamma_A^{hbr} + \Gamma_A^{syn}}{\Gamma_T}, 1\} \cdot \left(\frac{\Gamma_A^{syn}}{\Gamma_A^{hbr} + \Gamma_A^{syn}}\right)$$
$$\vartheta_T^{hbr} = \lambda max\{\frac{\Gamma_A^{hbr} + \Gamma_A^{syn}}{\Gamma_T}, 1\} \cdot \left(\frac{\Gamma_A^{hbr}}{\Gamma_A^{hbr} + \Gamma_A^{syn}}\right)$$

where the common component, $\lambda max\{\frac{\Gamma_A^{hbr}+\Gamma_A^{syn}}{\Gamma_T}, 1\}$, captures the total probability of meeting with an acquirer, and the weight $\frac{\Gamma_A^{syn}}{\Gamma_A^{hbr}+\Gamma_A^{syn}}$ and $\frac{\Gamma_A^{hbr}}{\Gamma_A^{hbr}+\Gamma_A^{syn}}$ captures the chance of meeting with a synergistic or hubristic acquirer. When the target meets with a synergistic acquirer, the gain is defined the same as that in the baseline model, and when it meets with a hubristic acquirer, it receives a premium of γ based on its stand-alone value, so the expected gain is $E[\gamma]V_{SA}(z_{i,t}, s_{i,t})$.

To compute the firm's market value, I retain the informational assumptions in the baseline model, with one more assumption added regarding the bid announcement. Specifically, I assume that when a bid is announced, the market can discern whether it is a synergistic acquisition or a hubristic acquisition. This assumption is not unreasonable. First, we do observe in the data that when some bids fail exogenously, the combined firm value increases, reflecting that the market recognizes the proposed acquisition may destroy value if consummated (so the market indeed knows that such deals are driven by hubris motives instead of synergy). Second, in the extended model with the estimated parameters, the hubristic acquirer set is far away from the synergistic acquirer set, so acquirer characteristics are also strong indicators of the takeover motives. Third, by assuming that hubris motives are perfectly observed by the market, the extended model maximizes the difference of market reactions to the two types of acquisitions. Doing so allows hubristic acquisitions to have the largest effect on model estimation and therefore provides an upper bound estimate of the potential bias in the baseline model, which serves the main purpose of this robustness check.

I denote $\mathcal{F}_{hbr}^{(n)}$ ($\mathcal{F}_{syn}^{(n)}$) as the market's information set associated with hubristic (synergistic) acquirers at stage $n = 2, 3, 4, 5$.[1] The market value of synergistic acquirers can be solved similarly as in the baseline model. I derive below the announcement return and the market value change upon exogenous bid failure for hubristic acquirers and for targets when they meet with hubristic acquirers, which will be used in computing the model-implied moments for the SMM. After a hubristic acquisition is announced, the market value for the hubristic acquirer and the target are

[1] Note that at stage 0 and 1, no bid announcement is made, so there is no need to distinguish hubristic acquirers from synergistic acquirers.

$$MV^{(2)}_{HAcq,t} = E\left[V_{SA}(z_{i,t}, s_{i,t})|\mathcal{F}^{(2)}_{hbr}\right] + \beta(1-\iota)E\left[\Sigma(z_{i,t}, s_{i,t}; z_{j,t}, s_{j,t}) - \gamma V_{SA}(z_{j,t}, s_{j,t})|\mathcal{F}^{(2)}_{hbr}\right] - C \quad \text{(G.5)}$$

$$MV^{(2)}_{Tar,t} = E\left[V_{SA}(z_{j,t}, s_{j,t})|\mathcal{F}^{(2)}_{hbr}\right] + \beta(1-\iota)\gamma E\left[V_{SA}(z_{j,t}, s_{j,t})|\mathcal{F}^{(2)}_{hbr}\right] - C \quad \text{(G.6)}$$

where $HAcq$ denotes the hubristic acquirer and $\mathcal{F}^{(2)}_{hbr} = \mathcal{F}^{(0)}_t \cup \{\ell_{i,t} = HAcq,\ \ell_{j,t} = Tar,\ \gamma\}$. Note that when the hubristic acquirer makes an offer to the target, offer premium γ in equation G.6 is drawn as a realization of the normal distribution $N(\mu_\gamma, \sigma_\gamma)$. The announcement returns for the hubristic acquirer and the target are:

$$r^{ann}_{HAcq,t} = \frac{MV^{(2)}_{HAcq,t} - MV^{(0)}_{i,t}}{MV^{(0)}_{i,t}} \quad \text{(G.7)}$$

$$r^{ann}_{Tar,t} = \frac{MV^{(2)}_{Tar,t} - MV^{(0)}_{j,t}}{MV^{(0)}_{j,t}} \quad \text{(G.8)}$$

If the hubristic acquisition is called off exogenously, the market values of the hubristic acquirer and target become

$$MV^{(3)}_{HAcq,t} = E\left[V_{SA}(z_{i,t}, s_{i,t})|\mathcal{F}^{(3)}_{hbr}\right] - C \quad \text{(G.9)}$$

$$MV^{(3)}_{Tar,t} = E\left[V_{SA}(z_{j,t}, s_{j,t})|\mathcal{F}^{(3)}_{hbr}\right] - C \quad \text{(G.10)}$$

Since there is no new information revealed in exogenous bid failure, $\mathcal{F}^{(3)}_{hbr} = \mathcal{F}^{(2)}_{hbr}$ hold. As a result, when a hubristic bid is terminated exogenously, the total value change for the combined firm is

$$\begin{aligned}\triangle MV^{(3)}_{HAcq,t} + \triangle MV^{(3)}_{Tar,t} &= MV^{(3)}_{HAcq,t} + MV^{(3)}_{Tar,t} - MV^{(2)}_{HAcq,t} - MV^{(2)}_{Tar,t} \\ &= -\beta(1-\iota)E\left[\Sigma(z_{i,t}, s_{i,t}; z_{j,t}, s_{j,t})|\mathcal{F}^{(2)}_{hbr}\right] \quad \text{(G.11)}\end{aligned}$$

Note that the combined firm value may rise upon exogenous bid termination if the hubristic bid is perceived to destroy value (i.e., $E\left[\Sigma(z_{i,t}, s_{i,t}; z_{j,t}, s_{j,t})|\mathcal{F}^{(2)}_{hbr}\right] < 0$).

H Other Robustness Checks

I present in this section more robustness checks that are not covered in the main paper. These exercises examine the sensitivity of model implications with respect to a few missing factors that are left out of the baseline model.

H.1 Comovement between productivity and seeds

Shocks to a firm's productivity and seeds are assumed to be uncorrelated in the baseline model, and I examine how different values of the correlation may alter the estimation results.

Table A.2 presents the parameter estimates and model implications in three scenarios with different values of correlation between shocks to z and s. The scenario with $\rho_{zs} = 0$ corresponds to the baseline model results. I experiment with two alternative assumptions of ρ_{zs} ($\rho_{zs} = 0.5$ and $\rho_{zs} = -0.5$) and reestimate the model with the assumed ρ_{zs}.

When $\rho_{zs} = 0.5$, the estimated volatility of seed shocks drop significantly from 0.632 to 0.509, and the volatility of productivity shocks increases. The model-implied revelation effects and merger gains are both reduced in magnitude. The intuition is as follows: A positive correlation makes the movement in productivity and seeds more coordinated, and therefore, firms receiving positive (negative) productivity shocks are also more likely to experience increases (decreases) in their stock of seeds. This increases the likelihood for targets to have positive announcement returns and decreases the likelihood for acquirers to have positive announcement returns. The main model parameters that control these two moments are σ_s and σ_z. As a result, these two parameters adjust toward the appropriate directions to force the model to fit the data again under the new value of correlation $\rho_{zs} = 0.5$. Overall, when the movement in seeds and productivity are positively correlated, firms are less likely to have substantially unbalanced productivity and seeds, and therefore M&As create less value, on average.

When $\rho_{zs} = -0.5$, firms in the economy face the opposite situation. Productive firms are now more likely to become seed-constrained, and the constraint is also more severe. As a result, takeover announcements reveal more information regarding firms' stand-alone value, and M&As create more value in the economy.

H.2 The sensitivity of θ to characteristics

In my baseline model, I assume that θ is constant across deals. Although it is a reasonable starting point, this parameter is likely to depend on some covariates, such as deal-specific or firm-specific characteristics. In a related work, Gorbenko and Malenko (2014) estimate bidders' winning slack and document significant covariation between bidders' valuation and targets' characteristics. Following their work, I also investigate how the estimate of θ in my model may depend on certain covariates.

There are three possible approaches to implement the SMM estimation while allowing model parameters to change with covariates. The first approach is to follow Gorbenko and Malenko (2014) and Albuquerque and Schroth (2014) and specify the parameter of interest as a function of covariates. This approach is powerful, because it directly quantifies the effect of each covariate on the parameter. The main constraint of this approach is that it is computationally intensive when the number of covariates is large. Since my baseline model already has 8 parameters, adding more parameters makes the estimation less feasible.

The second approach is to perform the SMM estimation in different subsamples sorted by the covariates, and the parameter estimates obtained from SMM may vary across subsamples, reflecting the dependence of parameter estimates on such covariates. This method is ideal when we explore the effect of one or two covariates on parameter estimates. When the number of covariates is large, however, partitioning subsamples significantly reduces the sample size.

Therefore, I use the third approach, developed in Taylor (2013). Let Θ denote the parameter of interest and X denote the characteristics, we can rewrite the sensitivity of Θ with respect to X as

$$\frac{\partial \Theta}{\partial X} = \frac{\partial \Theta}{\partial M} \frac{\partial M}{\partial X}$$

where the first term on the right-hand side is the sensitivity of parameter estimates to moments, and the second term is the sensitivity of moments to characteristics. The first term can be computed by disturbing the moments and reestimating the model parameters, and the second term can be computed from OLS regressions. As a result, a parameter is sensitive to certain characteristics only when the moments that help identify the parameter are sensitive to the characteristics.

Table A.3 presents the results. θ, which captures the acquirers' bargaining power, is estimated to be higher in horizontal mergers, in deals with small targets, and when acquirers and targets have moderate leverage. It does not appear to correlate much with acquirers' or targets' valuation ratio. These findings are consistent with those of Gorbenko and Malenko (2014), though their study builds on a different model and estimation technique. The magnitude of the coefficients are also economically sizable for some characteristics. For example, doubling the target firm size from its sample mean is associated with a decrease of θ by 0.149. Given the point estimate of θ is about 0.63, it represents a roughly 24% drop in acquirers' relative bargaining power. Also, acquirers in horizontal mergers seem to earn more and possess a bargaining power that is about 39% (0.245/0.63) higher than that of acquirers in non-horizontal mergers.

H.3 Method of payment

The payment method is an important factor left outside the model. There are several reasons why payment method might be relevant. First, in reality, the payment method may affect acquirers' capital structure and influence acquirers' future financing and operation. My model does not capture this effect, because it assumes that firms are all equity-financed and that there is no friction in dividend distribution or equity issuance. Hence, in the model, paying with cash or paying with equity are not influenced by firms' capital structure choice.

Second, the payment method is also related to possible misvaluation of acquirers or targets. For example, the market timing theory of M&As suggests that overvalued bidders may use their equity as cheap currency to purchase real assets from targets. There is also evidence showing that when targets are undervalued, bidders prefer using cash in the deals. My model is silent on misvaluation risk, because there is no information asymmetry between the acquirer and the target regarding each other's true value when they negotiate the offer price and merger clauses. As a result, equity payment and cash payment make no difference to the acquirer and the target in the model.

Target ownership is another factor that may affect acquirers' choice of payment method. If acquirers' large shareholders want to secure their majority position in the combined firm, they may prefer using cash instead of equity to acquire large targets with concentrated ownership. This factor, however, does not clearly relate to value-creation or split in M&As, and therefore, it does not necessarily bias my estimation.

To examine the impact of the payment method, one needs to consider both the acquirer's capital structure choice and the asymmetric information between acquirers and targets. Regarding the capital structure choice, paying with equity may imply that an acquirer is more financially constrained, which can be a new source of the negative revelation effect. Regarding the asymmetric information factor, paying with equity may signal acquirer's overvaluation risk, which leads to a negative revelation effect for acquirers too. In contrast, paying with cash may signal that the target is undervalued, which makes the revelation effect for targets more positive.

In general, adding the payment method to my model can help explain the empirical stylized fact that equity bidders, on average, suffer more than cash bidders on takeover announcements and that target announcements are higher in cash deals than in equity deals. I leave this extension to future research.

H.4 Economic recessions

I examine the model implications of economic recessions. Specifically, I use the estimated model as the laboratory and introduce into the simulation a negative aggregate shock to z so that 80% of firms' productivity is reduced. Firms' seeds are assumed to remain the same after the shock to z. I then track the transition path back to the steady state. Figure A.1 plots different variables of interest in the transition process. The first row shows the mean and standard deviation of z in this economy. The aggregate shock reduces the average z dramatically, and the average z gradually transits back to its pre-shock level after about 30 model periods. The aggregate shock reduces the standard deviation of z only slightly, because the aggregate shock is assumed to affect most firms to a similar extent. After the negative aggregate shock to z occurs, the number of firms searching as an acquirer drops significantly, while the number of firms searching as a target jumps up. This result is intuitive: When a firm's z drops much but its s remains the same, it becomes less likely to be seed-constrained. Moreover, firms that locate close to the target set before the aggregate shock may be dragged into the target set by the shock. Acquirer gains and target gains are both lower after the shock, and the reductions are moderate in magnitude. The revelation effects increase for both acquirers and targets. This is because after the aggregate shock to z, most firms become smaller. As shown in Panel (d) of Figure 2 in the paper, smaller acquirers are more likely driven by positive shocks to z and smaller targets are more likely driven by positive shocks to s, and they both have a positive revelation effect. As a result, the average revelation effects increase for both acquirers and targets post shock.

Overall, this exercise suggests that a large, negative aggregate shock to z may make most firms downsize. It increases the number of firms that seek to sell their assets and decreases the number of firms that look for making acquisitions. The probability of M&As drops, and the transaction values become smaller. Though the merger gains are lower, on average, the revelation effect is higher for both acquirers and targets. These features appear consistent with the periods of economic recessions.

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Table A.2: **Robustness Check: Correlation Between Productivity Shocks and Seed Shocks**

This table summarizes the parameter estimates and model implications with different values of correlation between shocks to productivity and seeds. The scenario with $\rho_{zs} = 0$ corresponds to the baseline model results. The parameter estimates panel reports the estimated model parameters when the correlation between shocks to productivity and seeds is set to different values; the model implication panel reports the model-implied acquirer announcement returns, revelation effects, and merger gains.

		$\rho_{zs} = 0.5$		$\rho_{zs} = 0$		$\rho_{zs} = -0.5$	
Notation	Parameter	Estimate	Std. err.	Estimate	Std. err.	Estimate	Std. err.
C	Search cost	3.220	0.434	2.861	0.413	2.821	0.410
θ	Acquirer's share of merger gains	0.613	0.036	0.629	0.038	0.630	0.038
λ	Arrival rate of matching	0.620	0.128	0.604	0.127	0.610	0.127
$\bar{s}$	Long-run mean of seeds	4.542	0.144	4.686	0.146	4.609	0.144
ρ_s	Persistence of seeds	0.861	0.010	0.860	0.010	0.855	0.011
σ_s	Standard deviation of shocks to seeds	0.509	0.025	0.632	0.029	0.775	0.034
ρ_z	Persistence of productivity	0.962	0.005	0.963	0.005	0.963	0.005
σ_z	Standard deviation of shocks to productivity	0.069	0.006	0.063	0.006	0.058	0.005

Model Implications	$\rho_{zs} = 0.5$	$\rho_{zs} = 0$	$\rho_{zs} = -0.5$
Acq. Ann. Return (%)	-0.79	-0.98	-0.77
Acq. Revelation Effect (%)	-3.30	-4.85	-5.78
Acq. Merger Gain (%)	2.51	3.87	5.01

Table A.3: **Robustness Check: Sensitivity of Parameter Estimate to Characteristics**

This table presents the sensitivity of acquirers' share of merger gains, θ, with respect to deal and firm characteristics. *Horizontal* is a dummy variable equal to one if the acquirer and the target are in the same Fama-French 48-industry, and zero otherwise; $ln(MV_{Acq})$ and $ln(MV_{Tar})$ are the logarithm of acquirers' and targets' market value 22 trading days before bid announcements; Q_{Acq} and Q_{Tar} are the market-to-book ratios of acquirers and targets; Lev_{Acq} and Lev_{Tar} are acquirers' and targets' leverage, and $Lev^2{}_{Acq}$ and $Lev^2{}_{Tar}$ are the square of leverage. Standard errors are reported in the parentheses.

Sensitivity of θ with Respect to Deal/Firm Characteristics								
$Horizontal$	$ln(MV_{Acq})$	$ln(MV_{Tar})$	Q_{Acq}	Q_{Tar}	Lev_{Acq}	$Lev^2{}_{Acq}$	Lev_{Tar}	$Lev^2{}_{Tar}$
0.245	1.050	-0.149	0.037	-0.004	0.258	-0.375	0.092	-0.250
(0.063)	(0.025)	(0.029)	(0.026)	(0.022)	(0.453)	(0.567)	(0.445)	(0.504)

Figure A.1: **Transition Path**

This figure shows the transition path of the model economy when a negative aggregate shock to z hits 80% of firms. The model parameters are kept the same as in the baseline estimation, and I assume firms possess the same conjecture as they do in the steady state. Average z and Stdev z are the mean and standard deviation of z in the economy; Search as acq and Search as tar are the population of firms that actively search in the market as a potential acquirer or target; Acq Gain and Tar Gain are the average merger gains for acquirers and targets; and Acq Revelation and Tar Revelation are the average revelation effect for acquirers and targets. The x-axis represents the model period (in years) in the simulation, and $t = 0$ is the year when the aggregate shock occurs.