Judged by the Company You Acquire

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Abstract

Acquirers' target choice can systematically reveal their technological gaps. I measure this gap as the similarity between the target's technology and the technological frontier of the acquirer's industry. Acquirers with larger gaps experience more negative market revaluations, as reflected in more negative announcement returns. This effect is present when the target is public, but not when it is private. These findings offer a new explanation for the observed disparity in acquirer returns between public and private targets: private targets are less transparent and therefore less likely to reveal the acquirer's technological gaps, unlike their public counterparts.

Keywords: Mergers and acquisitions, revaluation, technological gap, target selection

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1 Introduction

A long-standing puzzle in the mergers and acquisitions (M&A) literature is that acquirer returns upon acquisition announcements are, on average, neutral to negative (Akbulut & Matsusaka, 2010; Betton, Eckbo, & Thorburn, 2008; Moeller, Schlingemann, & Stulz, 2005), yet acquirers do not systematically underperform post-acquisition (Fama, 1998; Franks, Harris, & Titman, 1991; Mitchell & Stafford, 2000; Savor & Lu, 2009). This challenges the widely adopted assumption that announcement returns primarily reflect a deal's quality. Adding to this puzzle is a stark cross-sectional difference in announcement returns between acquirers of public and private targets: negative for the former, but positive for the latter (Ang & Cheng, 2006; Capron & Shen, 2007; Chang, 1998; Faccio, McConnell, & Stolin, 2006; Fuller, Netter, & Stegemoller, 2002; Hansen & Lott, 1996). This paper reconciles these findings by examining a component in acquirer returns that does not reflect deal quality.

Hietala, Kaplan, and Robinson (2002) is among the earliest studies to decompose announcement returns into a synergy component and a revaluation component, with the latter reflecting the market's updated assessment of the transacting party's standalone value in light of information revealed by the announcement. A recent study shows that the revaluation component is of first-order importance, driving over half of the cross-sectional variation in acquirer returns (Wang, 2018). In spite of it, the literature has recognized revaluations almost exclusively in the context of the method of payment—stock payments may signal overvalued acquirers (Myers & Majluf, 1984; Shleifer & Vishny, 2003), and trigger negative market reactions (Fuller, Netter, & Stegemoller, 2002; Moeller, Schlingemann, & Stulz, 2004; Travlos, 1987). Yet, it remains unclear whether and how other aspects of acquisitions drive revaluations.

This paper introduces a new revaluation mechanism: the nature of the target may reveal information about the acquirer's competitive standing. Specifically, I hypothesize that when a target's technology closely resembles the technological frontier of the acquirer's industry, the market interprets the acquisition as an attempt to close a technological gap, prompting a downward revaluation of the acquirer. I refer to such acquirers as *gap bidders*: acquirers whose choice of target unintentionally signals their weak technological position.

Technology acquisitions provide a fertile setting to study this mechanism. First, technological innovation is a well-established driver of M&A activity (Bena & Li, 2014; Betton, Eckbo, & Thorburn, 2008; Higgins & Rodriguez, 2006; Phillips & Zhdanov, 2013). Second, firms' technological capabilities are inherently difficult to observe due to long development cycles and demanding knowledge requirements. Since revaluations arise from information that surprises the market, technology-oriented acquisitions offer a particularly suitable laboratory for investigating informational effects.

To formalize this intuition, I model acquisition decisions in the context of technological investment in response to industry-wide technological progress—conceptualized as a shock that shifts the technological frontier. Due to firms' distinct technological bases, they are differently positioned to adapt to the shock. I capture this heterogeneity through differences in technological endowments, which translate into varying gaps to the frontier. This assumption reflects the Schumpeterian view that technological progress is inherently disruptive and can reorder firms' positions within an industry (Schumpeter, 1942)

Firms can obtain additional technology through two channels: in-house development (R&D) and acquisitions. In-house development is cost-efficient for small-scale investments but becomes increasingly expensive as the scale grows, due to its time-consuming nature and the delays it causes in commercialization. In contrast, acquisitions enable immediate deployment, making them well-suited for large-scale investments. However, the associated fixed costs can be prohibitively high for small-scale investments.

This cost structure gives rise to a pecking-order strategy: firms with larger technological endowments (or smaller gaps) rely exclusively on in-house development (*pure in-house developers*), while those with smaller endowments (or wider gaps) eventually resort to acquisitions (*gap bidders*). These predictions parallel the logic of capital investment documented by Jovanovic and Rousseau (2002). It follows that firms with larger technological gaps—and thus lower intrinsic value—are the ones most likely to pursue acquisitions.

If the market cannot perfectly observe firms' technological endowments, it tends to undervalue pure in-house developers and overvalue gap bidders ex ante. Upon an acquisition announcement, the quantity of technology units acquired reveals the scale of the acquirer's technological gap. As a result, gap bidders experience downward revaluations upon acquisition announcements.

The model further explores the scenario where the acquisition serves as a noisy signal about the acquirer's technological standing. Intuitively, the market can extract more reliable inferences about the acquirer when the target provides a less noisy—hence more informative—signal than the acquirer. Thus, revaluation is predicted to be stronger when the target is more transparent relative to the acquirer.

To test the model's predictions, I construct a measure of revealed technological gaps leveraging patent data from the U.S. Patent and Trademark Office (USPTO). First, I use the target's patent portfolio to proxy its technology and the aggregate patent portfolio of the acquirer's industry peers to proxy the technological frontier of the acquirer's industry. Second, I measure the similarity between these two patent portfolios. This measure captures the extent to which the acquirer is "buying the frontier": the higher the similarity, the stronger the signal that the acquirer is in a weak technological position and seeks to close the gap through the acquisition.

I draw a sample of 1,044 public-target and 962 private-target acquisitions involving publicly listed acquirers between 1990 and 2020 from SDC. Among public-target deals, a strong negative association between acquirer cumulative abnormal returns (CARs) and the revealed gap measure emerges: a one-standard deviation increase in the measure is associated with a 0.83–1.83 percentage-point (11–22% standard deviation) decline in CARs—an effect larger in magnitude than that of the method of payment. In contrast, the relationship is absent in private-target acquisitions. This asymmetry is consistent with the model's prediction: since private targets are opaque, the market cannot reliably infer the acquirer's technological gap through the target.

To empirically substantiate the mechanism, I proxy corporate opacity using bid-ask spreads and analyst following, and measure acquirer-target relative opacity. Among public-target deals, revaluation occurs almost exclusively when the acquirer is more opaque than the target, with the effect intensifying as the opacity gap widens. In the case of private-target deals, I find evidence of negative revaluation only within the subset of deals involving exceptionally transparent targets, identified by bond issuance prior to the acquisition announcement.

Next, I decompose the revealed gap measure into two components: one predicted by well-documented acquisition antecedents, and a residual orthogonal to them. Regression results show that only the residual component is significantly associated with acquirer CARs. This finding suggests that the negative correlation between acquirer returns and revealed gaps is fully attributable to unexpected information revealed through the target choice.

For robustness, I rule out several alternative explanations, including overpayment, partially priced-in acquisition gains due to pre-announcement anticipation, and dissynergies arising from acquirer–target mismatch. I also demonstrate that the main results are not sensitive to the granularity of the patent classification scheme used to construct the *GapSignal* measure. As an extension, I explore the inverse scenario—whether the market infers the target's technological gap from the acquirer's observable technological profile, and find only weak and suggestive evidence.

This paper is related to several strands of the literature. First, it contributes to the literature on revaluation in M&As. The most closely related study is Wang (2018), which models M&A transactions as a process of reallocating complementary assets in a two-sided search market and structurally decomposes announcement returns into components reflecting anticipation, revaluation, and synergies. While that framework offers valuable insights, it relies on simplifying assumptions that abstract away from specific economic mechanisms. This paper complements that approach by unpacking the "black box" of revaluation and grounding the analysis in a concrete and economically meaningful context—technological gaps, thus providing a clearer understanding of how and why revaluations occur in M&As. Besides, Blouin, Fich, and Tran (2020) show that firms acquiring R&D-intensive targets in response to tax incentives may inadvertently signal a lack of internal R&D capabilities. Jacobsen (2014) finds that withdrawing from overpriced M&A deals can serve as a signal of CEO quality, prompting positive revaluations. This paper complements these works by documenting a more direct revelation mechanism that emerges in a broader and more commonly observed strategic context.

Earlier studies of acquirer revaluation have primarily focused on the method of payment as the key revelation channel. This paper contributes to that literature by introducing a novel revelation mechanism rooted in the acquirer's choice of target. More broadly, the paper also relates to a growing literature on revaluation of targets (Malmendier, Opp, & Saidi, 2016) and industry peers (Cai et al., 2024; Derrien et al., 2023) in response to M&A announcements.

Second, I contribute to research addressing the disparity in announcement returns between public- and private-target acquisitions. For example, Chang (1998) and Fuller, Netter, and Stegemoller (2002) suggest that private sellers receiving stock may become blockholders in the acquiring firm, thereby enhancing post-deal monitoring and increasing acquirer valuation. Ang and Kohers (2001) and Chang (1998) further posit that private targets may accept lower acquisition premiums due to their illiquidity, enabling acquirers to capture more value. Hansen and Lott (1996) argue that in public-target deals, acquirer shareholders can hedge the risk of overpayment by also holding shares in the target—an option unavailable in private-target transactions. Studying a sample of Western European acquisitions, Faccio, McConnell, and Stolin (2006) conclude that none of these theories fully explains the observed acquirer return disparity between public- and private target deals.

Complementary to these existing explanations, my results suggest that the divergence in returns may also stem from the differential informativeness of the target. Public targets, being more transparent, allow the market to extract more inferences about the acquirer than their private counterparts.

Third, this paper relates to a broader literature on acquirer–target complementarity, which explores synergies across dimensions such as product markets (Hoberg & Phillips, 2010; Jia & Sun, 2022), human capital (Lee, Mauer, & Xu, 2018), and assets in a general sense (Rhodes-Kropf & Robinson, 2008; Rhodes-Kropf, Robinson, & Viswanathan, 2005). In a closely related but distinct context, Bena and Li (2014) show that technological overlap between acquirers and targets can generate synergies. This paper emphasizes technological complementarity as a motive for acquisition but highlights an informational implication:

target choice can reveal hidden traits of the acquirer that shape the acquisition decision. This perspective opens avenues for future research on the informational dynamics of M&As, particularly in relation to other forms of acquirer–target complementarity.

Lastly, this paper reinforces a growing view that challenges the uncritical use of announcement CARs as proxies for value creation in M&A research (Ben-David et al., 2025). The findings suggest that CARs may not simply be a noisy measure of deal NPV, but could be systematically biased. In particular, when firms pursue acquisitions to address competitive disadvantages, the market reactions may reflect a downward revaluation of the acquirer's standalone value. As a result, CARs may systematically understate the deals' true net present value (NPV).

The rest of the paper is organized as follows. Section 2 presents a formal model and derives testable predictions. Section 3 describes the data, outlines the empirical strategy, and defines the key variables. Section 4 reports the main empirical results and discusses the findings. Section 5 addresses alternative explanations, conducts robustness checks, and explores extensions. Section 6 concludes.

2 Theoretical framework

In this section, I present a simple model to formalize the hypotheses of the paper. I first model firms' endogenous decision to close technological gaps through acquisitions. Next, I introduce informational frictions into the framework and analyze how they shape the market's inference process. Finally, I state the paper's main hypotheses.

2.1 Acquisitions as endogenous decisions

To set the stage, consider a static economy populated by a continuum of profit-maximizing firms. Each firm is endowed with $z \geq 0$ units of technology as an input to produce for a single period, after which all proceeds are distributed to investors. For simplicity, I abstract away from other inputs—such as capital and labor—and solely focus on technology. The production function is given by

$$Q(z) = \kappa z^{\alpha}, \tag{1}$$

where $\kappa > 0$ captures productivity, and $\alpha \in (0, 1)$ ensures decreasing returns to scale.

Firms can invest in $x \geq 0$ additional units of technology internally through in-house development at a per-unit price $p > 0$, and $y \geq 0$ units externally through acquisitions at a per-unit price $p + f$, where $f > 0$ captures search costs and advisory fees associated with participating in the M&A market. Installing the additional technology units entails further costs: the per-unit installation cost is fixed for externally acquired units, but convex for internally developed ones. This reflects the idea that in-house development is time-consuming and subject to diminishing returns, whereas acquisitions allow for immediate deployment. The total cost of technological investment is given by

$$c(x, y) = \underbrace{px + (p + f)y}_{\text{purchase costs}} + \underbrace{\beta(x^{\phi} + y)}_{\text{installation costs}}, \tag{2}$$

where $\beta > 0$ governs the magnitude of installation costs, and $\phi > 1$ ensures the per-unit installation cost in convex in x. In the presence of technological investment, a firm's value is thus given by

$$V = Q(z + x + y) - c(x, y). \tag{3}$$

The interior solution that maximizes V is given by

$$x^* = \left(\frac{f + \beta}{\beta\phi}\right)^{\frac{1}{\phi-1}}, \tag{4}$$

$$y^* = \left(\frac{\alpha\kappa}{p + f + \beta}\right)^{\frac{1}{1-\alpha}} - z - x^*. \tag{5}$$

x^* is the efficient level of internal investment where the marginal cost of internal investment equals that of acquisitions. It increases with the acquisition-related fixed cost f and the baseline installation cost β, but decreases with ϕ, which governs how rapidly marginal installation costs escalate with internal investment x. Notably, x^* does not depend on the per-unit price of technology p, but rather on the price difference between internal and external options. It is also independent of the technological endowment z since the cost of internal investment does not vary with it.

Intriguingly, the efficient levels of internal investment x^* and acquisitions y^*, and the firm's technological endowment z always sum up to a constant Z:

$$Z = x^* + y^* + z = \left(\frac{\alpha\kappa}{p + f + \beta}\right)^{\frac{1}{1-\alpha}}. \tag{6}$$

Z represents the efficient level of technology that *all* firms aim to achieve, regardless of their technological endowment. It arises endogenously from the cost structure and production parameters, making it a natural benchmark for the technological frontier and a logical upper bound for firms' technological endowment. Accordingly, I define a firm's technological gap as the distance between the technological frontier Z and the firm's technological endowment

z:

$$G = Z - z. \tag{7}$$

The optimization problem can then be reframed to one where firms maximize value by choosing x and y to close the technological gap G, such that $x + y = G$. It is also noteworthy that the parameter ϕ appears in x^* and y^*, but not in Z (hence not in G). This indicates that differences in marginal installation costs between the internal and external options affect how firms split the total technological investment—equal to G—into the two options, but not the magnitude of G itself.

Lastly, incorporating the boundary conditions $x, y \geq 0$, the optimal strategy can be expressed as functions of the technological gap G:

$$x = \begin{cases} \text{G} & \text{if } G \in [0, x^*], \\ x^* & \text{if } G \in (x^*, Z]; \end{cases} \tag{8}$$

$$y = \begin{cases} 0 & \text{if } G \in [0, x^*], \\ G - x^* & \text{if } G \in (x^*, Z]. \end{cases} \tag{9}$$

Figure 1 visualizes the piecewise structure of Equations (8) and (9). The prediction is clear: firms follow a *pecking order* in closing their technological gap. Specifically, firms initially rely solely on in-house development, up to the threshold x^*, and resort to acquisitions only after exhausting their internal capacity. Following this strategy, the resulting firm value can be expressed as a function of G:

$$V(G) = \begin{cases} Q(Z) - c(G, 0) & \text{if } G \in [0, x^*], \\ Q(Z) - c(x^*, G - x^*) & \text{if } G \in (x^*, Z], \end{cases} \tag{10}$$

which decreases monotonically in G. These equations imply that all firms ultimately operate at the technological frontier. Cross-firm differences in value arise entirely from the costs associated with their respective strategies in response to varying technological gaps.

2.2 Informational frictions and revaluations

2.2.1 Modeling market reactions

In this section, I derive the market reactions experienced by gap bidders—firms with a technological gap $G > x^*$, for whom acquisitions are part of the optimal strategy. To begin with, I assume each firm's technological endowment z is privately known, while its ex ante distribution is common knowledge. The technological frontier Z and the threshold x^* are also common knowledge. Mechanically, the technological gap $G = Z - z$ is privately known, and its ex ante distribution is common knowledge.

Let $F(\cdot)$ denote the cumulative distribution function (CDF) of G. With probability $F(x^*)$, a firm is a pure in-house developer that does not undertake acquisitions ($G \leq x^*$). The average firm value among pure in-house developers is given by $\mathbb{E}[V(G) \mid G \leq x^*]$. Conversely, with probability $1 - F(x^*)$, a firm is a gap bidder ($G > x^*$). The average firm value among gap bidders is given by $\mathbb{E}[V(G) \mid G > x^*]$. Since the market cannot observe firms' technological gap G, its ex ante expectation of firm value is identical for pure in-house developers and gap bidders. This expected value is given by

$$\mathbb{E}[V(G)] = F(x^*) \cdot \mathbb{E}[V(G) \mid G \leq x^*] + [1 - F(x^*)] \cdot \mathbb{E}[V(G) \mid G > x^*], \tag{11}$$

which is a weighted average of the expected firm values for pure in-house developers and gap bidders, respectively.

Gap bidders reveal their technological gap $G > x^*$ through the very act of announcing an acquisition. Upon observing the target's technology—namely y, the market infers the acquirer's technological gap $G = y + x^*$, and revises its valuation accordingly. The average market reaction—i.e., abnormal return (AR)—towards an acquisition announcement is given by

$$\begin{aligned}\mathbb{E}[AR] &= \frac{\mathbb{E}[V(G) \mid G > x^*] - \mathbb{E}[V(G)]}{\mathbb{E}[V(G)]} \\ &= \frac{F(x^*) \cdot (\mathbb{E}[V(G) \mid G > x^*] - \mathbb{E}[V(G) \mid G \leq x^*])}{\mathbb{E}[V(G)]},\end{aligned} \tag{12}$$

which is the difference between the average value among gap bidders and the ex ante expected value, scaled by the latter. Given that $V(G)$ is monotonically decreasing in G, it follows that

$$\mathbb{E}[V(G) \mid G > x^*] < \mathbb{E}[V(G) \mid G \leq x^*], \tag{13}$$

and therefore, the average market reaction to a gap bidder's acquisition announcement is negative (Equation (12)). In addition, it is straightforward that the technological gap and ARs are negatively correlated across individual gap bidders, provided that $V(G)$ is strictly decreasing in G:

$$AR(G) = \frac{V(G) - \mathbb{E}[V(G)]}{\mathbb{E}[V(G)]} \quad G \in (x^*, Z]. \tag{14}$$

2.2.2 Decomposing market reactions

The market reactions to acquisition announcements, as described in Equations (12) and (14), consist of two components: revaluations triggered by the revelation of the acquirer's technological gap, and (unexpected) synergies arising from the complementary technology between the acquirer and the target. Next, I decompose the AR into these two components.

First, revaluations represent the change in the market's assessment of a firm's standalone value. I define the standalone value by setting $y = 0$ while x at its optimal level in Equation (3):

$$V^S(G) = \begin{cases} Q(Z) - c(G, 0) & \text{if } G \in [0, x^*], \\ Q(z + x^*) - c(x^*, 0) & \text{if } G \in (x^*, Z]. \end{cases} \tag{15}$$

Notice that $z = Z - G$. Intuitively, this definition reflects a hypothetical scenario where the acquirer's technological gap gets revealed without the acquisition actually taking place. In this scenario, gap bidders ($G \in (x^*, Z]$) cannot reach the technological frontier, resulting in productivity losses. Then, I decompose the AR experienced by a gap bidder, as shown in Equation (14), as follows:

$$AR(G) = \underbrace{\frac{V(G) - V^S(G)}{\mathbb{E}[V(G)]}}_{\text{total synergies}} - \underbrace{\frac{\mathbb{E}[V(G)] - \mathbb{E}[V^S(G)]}{\mathbb{E}[V(G)]}}_{\text{expected synergies}} + \underbrace{\frac{V^S(G) - \mathbb{E}[V^S(G)]}{\mathbb{E}[V(G)]}}_{\text{revaluations}}. \tag{16}$$

The first term represents the difference between a gap bidder's post-acquisition value and its standalone value, capturing the total synergies from the acquisition. The second term reflects the market's ex ante expectation of the first term, that is, the expected synergies, as the market anticipates that some firms will engage in acquisitions. The final term represents the difference between a firm's standalone value and the market's ex ante expectation of that value, thus reflecting revaluations.

Differentiating Equation (16) with respect to G gives the marginal effect of the components:

$$\frac{dAR(G)}{dG} = \underbrace{\frac{Q'(z + x^*) - (p + f + \beta)}{\mathbb{E}[V(G)]}}_{\text{marginal synergies}} - \underbrace{\frac{Q'(z + x^*)}{\mathbb{E}[V(G)]}}_{\text{marginal revaluations}}, \tag{17}$$

where $Q'(z) = \alpha\kappa z^{\alpha-1}$ is the derivative of $Q(z)$, as given by Equation (1), and reflects the marginal product of technology. The term $p + f + \beta$ represents the marginal cost of acquisitions. It is easy to demonstrate that the marginal synergies are positive. This follows from diminishing returns to scale, which implies that $Q'(z)$ decreases in z. At the technological frontier, the marginal product equals the marginal cost of acquisitions: $Q'(Z) = p + f + \beta$. Since $Z > z + x^*$, it follows that $Q'(z + x^*) > p + f + \beta$. Positive marginal synergies suggest that a larger technological gap boosts unexpected synergies, driving market reactions upward. However, marginal revaluations outweigh this effect, leaving the net outcome reflecting only the marginal cost of acquisitions. This asymmetry arises because incremental synergies are penalized due to extra acquisition expenses, whereas revisions of the standalone value do not involve such a penalty.

2.2.3 Acquisitions as noisy signals

Earlier analyses assume that the target's technology perfectly signals the acquirer's technological gap. In reality, these signals are likely noisy for two reasons: (a) acquisitions often serve purposes beyond closing technological gaps, and (b) the target's technology can be difficult to observe.

Therefore, it is more realistic to assume that both the acquirer and the target provide noisy signals about the acquirer's technological gap G. The acquirer's signal shapes the ex ante belief about G, while the target's signal improves accuracy. For analytical simplicity, I assume these two signals follow a joint normal distribution:

$$\begin{bmatrix} G^A \\ G^T \end{bmatrix} \sim \mathcal{N}\left(G, \begin{bmatrix} \sigma_A^2 & \rho\sigma_A\sigma_T \\ \rho\sigma_A\sigma_T & \sigma_T^2 \end{bmatrix}\right), \tag{18}$$

where G^A denotes the signal derived from the acquirer, and G^T denotes the signal derived from the target. The parameters σ_A^2 and σ_T^2 represent the variances of the noise in the acquirer and target signals, respectively, while ρ captures the correlation between their noise.

I define the combined signal as a weighted average of G^A and G^T: $G^{AT} = w^A G^A + (1 - w^A)G^T$. The weight w^A that minimizes the variance of G^{AT} and the respective variance are given by

$$w^A = \begin{cases} \dfrac{\sigma_T^2 - \rho\sigma_A\sigma_T}{\sigma_A^2 + \sigma_T^2 - 2\rho\sigma_A\sigma_T} & \text{if } \rho \in (-1, 1), \\ 1 & \text{if } \rho = \pm 1 \text{ and } \sigma_A^2 \leq \sigma_T^2, \\ 0 & \text{if } \rho = \pm 1 \text{ and } \sigma_A^2 > \sigma_T^2; \end{cases} \tag{19}$$

$$\sigma_{AT}^2 = \begin{cases} \dfrac{\sigma_A^2\sigma_T^2\left(1 - \rho^2\right)}{\sigma_A^2 + \sigma_T^2 - 2\rho\sigma_A\sigma_T} & \text{if } \rho \in (-1, 1), \\ \min\left\{\sigma_A^2, \sigma_T^2\right\} & \text{if } \rho = \pm 1. \end{cases} \tag{20}$$

Notably, when the two signals are perfectly correlated ($\rho = \pm 1$), they are collinear, and the variance of the combined signal collapses to that of the less noisy one.

Based on the assumptions above, the average AR experienced by a gap bidder upon the acquisition announcement is given by

$$AR = \frac{\mathbb{E}_{AT}[V(G)] - \mathbb{E}_A[V(G)]}{\mathbb{E}_A[V(G)]}, \tag{21}$$

where $\mathbb{E}_A[\cdot]$ denotes expectations based on the acquirer signal, and $\mathbb{E}_A[\cdot]$ based on the combined signal. In other words, the AR reflects the incremental information provided by the target.

To capture the relative level of noise in the signals derived from the acquirer and the target, respectively, I define a normalized measure:

$$\text{Relative opacity} = \frac{\sigma_A^2 - \sigma_T^2}{(\sigma_A^2 + \sigma_T^2) \cdot 0.5}. \tag{22}$$

I label the measure as *relative opacity* to reflect the intuition that more opaque firms provide noisier signals. The measure ranges within $[0, 2]$ and takes values greater than zero when the acquirer is more opaque ($\sigma_A^2 > \sigma_B^2$), and less than zero when the target is more opaque ($\sigma_A^2 < \sigma_B^2$).

To examine the quantitative relationship between ARs, the strength of noise, and the correlation between noise, I perform a numerical simulation, randomly selecting σ_A^2 and σ_T^2 from a uniform distribution for three level of $\rho \in \{0, 0.5, 1\}$.[1] For each round of simulation, I record the average AR experienced by gap bidders and the relative opacity assumed.

Figure 2 plots average ARs against relative opacity across different levels of ρ. The figure shows that revaluation becomes more negative—hence stronger—when the target is relatively more transparent (to the right), and flattens when the acquirer is more transparent (to the left). Notably, as signal correlation ρ approaches 1, the two signals become collinear, and the market solely relies on the less noisy one, which is manifested as a sharp cusp in the curve where the acquirer and the target are equally transparent. While this behavior may seem extreme, it is not implausible in practice. Firms tend to disclose information selectively rather than randomly, often following a similar hierarchy—from mandated disclosures, to voluntary disclosures, and finally to proprietary or confidential information. As a result, firms' disclosures may be largely overlapping and only incrementally informative along this hierarchy.

Based on the analyses above, the following two hypotheses follow.

Hypothesis 1. *The market revalues an acquirer based on the information inferred from its*

[1] Other parameters are calibrated as follows: $\sigma_A^2, \sigma_B^2 \sim \mathcal{U}(0, 0.05)$, $\kappa = 1$, $\alpha = 0.25$, $p = \beta = 0.1$, $f = 0.05$, and $\phi = 2$. Notably, G is not defined beyond $[0, Z]$. Therefore, the distributions of G^A and G^{AT} are truncated over $[0, Z]$ in numerical simulations.

target choice. Specifically, there is a negative relationship between the revaluation the acquirer experiences and the technological gap signaled by the acquisition. On average, this revaluation tends to be systematically negative.

Hypothesis 2. *The intensity of revaluation is moderated by the relative opacity between the acquirer and the target. When the target is more transparent than the acquirer, the market assigns greater weight to the target as an information source when inferring the acquirer's technological gap, resulting in stronger revaluation. When the acquirer is relatively more transparent, the target contributes less to the inference, and the revaluation effect is correspondingly weaker.*

3 Data and methodology

3.1 Sample construction

To test the hypotheses, I construct a sample of announced acquisitions involving publicly listed acquirers between 1990 and 2020, using data from SDC via Wharton Research Data Services (WRDS). I supplement this sample with trading data from CRSP, financial data from COMPUSTAT, and patent data from the USTPO. Table A1 summarizes the sample selection process, including the filters applied and the number of observations remaining at each step. The final sample includes 1,044 public-target acquisitions and 962 private-target acquisitions.

Notably, I exclude acquisitions in which the target is a subsidiary, as I cannot reliably identify which patents filed under the parent company are transferred with the subsidiary. This exclusion is important because the analysis relies on patent portfolios to quantify firms' technological profiles.

To reflect industry-wide technological dynamics, I compile a broader sample of public and private companies by combining the universes of COMPUSTAT and CapitalIQ companies. Supplemented with hand-collected Standard Industrial Classification (SIC) codes for CapitalIQ firms, the final sample consists of 235,376 distinct companies, both public and private.

To characterize the technological profiles of all sample firms, I implement a frequency-based name-matching algorithm following Hall, Jaffe, and Trajtenberg (2001) to link patents to firms.[2] In total, I successfully link approximately 3 million patents to companies in the combined sample.[3] Of the linked patents, approximately 63% are contributed by public

[2] Further technical details are provided in Appendix A.1.

[3] There are two types of patents: utility patents and design patents. According to the USTPO, a utility

companies, 35% by private firms, and the remainder by institutions such as investment funds and universities. Overall, the linked patents account for about 40% of all patents filed globally by companies, individuals, and other entities between 1980 and 2020 with the USTPO, ensuring the representativeness of the patent sample.

It is noteworthy that only a subset of firms actively engage in patenting activities. As a result, the final sample is best understood as one comprising technology-oriented acquisitions.

3.2 Research design

The goal of the empirical strategy is to quantify an acquirer's technological gap as signaled by the target firm's technological profile, and to examine how this signal correlates with the stock market reactions to acquisition announcements. I first quantify firms' technological profiles leveraging patent data. Then, I construct a measure for acquirers' revealed technological gaps. Next, I describe the dependent variables—i.e., cumulative abnormal returns (CARs) around acquisition announcements, proxies for corporate opacity, and control variables. Lastly, I present and discuss descriptive statistics of the sample.

3.2.1 Quantifying technological profiles

To characterize a firm's technological profile, I rely on its patent portfolio. Patents are a valuable source of information for two main reasons. First, to be granted a patent, an invention must demonstrate real-world applicability, novelty over all prior art, and a non-obvious contribution beyond the knowledge of a skilled practitioner in the field. In this sense, patented inventions capture the technological frontier at the time of filing. Second, patents confer temporary monopolistic rights (typically lasting up to ten years) that allow the firm to exclusively commercialize the protected inventions. These rights often translate into substantial economic value. Indeed, a rich literature has documented patents' value effect.[4]

Patent classification codes are commonly used by researchers to identify technological fields.[5] In this paper, I employ the Cooperative Patent Classification (CPC) codes for this purpose. The CPC scheme follows a hierarchical structure that becomes increasingly granular at lower levels. I focus on the *class* level, which groups patents into 137 distinct technological

patent protects the way an article is used and works (35 U.S.C. §101), while a design patent protects the way an article looks (35 U.S.C. §171). This paper focuses exclusively on utility patents, as they better reflect the technological content of innovation.

[4]See, for example, Farre-Mensa, Hegde, and Ljungqvist (2020), Hall, Thoma, and Torrisi (2007), Kogan et al. (2017), and Pakes (1985).

[5]See, for example, Hall, Jaffe, and Trajtenberg (2001), Hegde, Herkenhoff, and Zhu (2023), and Seru (2014).

classes.[6] For robustness, I also replicate the main analysis using the *subclass* level, comprising 680 categories. The results remain both qualitatively and quantitatively similar.

For each firm i in year t, I extract all granted patents filed by the firm over the preceding 10 years (from year $t-1$ through year $t-10$). Then, I count the number of patents that fall into each of the 137 patent classes and construct a 137-dimensional vector $\mathbf{P}_{it} = (p_{it}^1, p_{it}^2, \ldots, p_{it}^{137})$, where each element p_{it}^j represents the number of patents in class j. Additionally, I denote the patent vectors for acquirers and targets as $\mathbf{P}_{it}^{Acq}$ and $\mathbf{P}_{it}^{Tar}$, respectively. The $\mathbf{P}$-vector describes the distribution of a firm's past patenting activity across technological classes and serves as a proxy for the firm's technological orientation.

Furthermore, for each acquirer, I characterize the technological frontier of its industry as of the year preceding the acquisition announcement. To do so, I aggregate the $\mathbf{P}$-vectors across all firms operating in the same two-digit SIC industry as the acquirer. To avoid endogeneity, I exclude both the acquirer and the target—if the target operates in the same two-digit SIC industry—from this calculation. The resulting vector that defines the industry technological frontier for acquirer i in year t is

$$\mathbf{P}_{it}^{AInd} = \sum_{k \in S_i} \mathbf{P}_{kt}, \tag{23}$$

where S_i denotes the set of firms in acquirer i's 2-digit SIC industry, excluding the acquirer and, if applicable, the target.

3.2.2 Measuring revealed technological gaps

Acquirers' technological gaps are not directly observable. As established in Section 2, the market can infer an acquirer's technological gap based on the technological profile of its acquisition target. Following this logic, I capture the acquirer's revealed technological gap as the degree to which the target's technological profile resembles the technological frontier of the acquirer's industry. A larger similarity indicates that the acquirer seeks to "buy the frontier," hence signaling its weak technological standing. I label the resulting measure as the *GapSignal* score.

Leveraging patent-based measures, I define the *GapSignal* score as the cosine similarity between the target's patent vector $\mathbf{P}_{it}^{Tar}$ and the acquirer's industry frontier $\mathbf{P}_{it}^{AInd}$:

$$GapSignal_{it} = \frac{\mathbf{P}_{it}^{Tar} \cdot \mathbf{P}_{it}^{AInd}}{\|\mathbf{P}_{it}^{Tar}\| \cdot \|\mathbf{P}_{it}^{AInd}\|}, \tag{24}$$

[6] The CPC scheme evolves as new technologies emerge. All CPC codes used in this paper reflect the version as of the end of 2023 and are applied retroactively to earlier patents.

where $\|\cdot\|$ denotes the Euclidean norm of a vector. Cosine similarity captures the angular alignment between two vectors while ignoring their magnitude, and thus reflects technological orientations rather than overall patenting intensity. This choice is grounded in the fact that the number of patents a firm holds may reflect strategic patenting behavior, rather than its technological capabilities. For instance, firms may file patents defensively or preemptively in response to competitive pressure (Bessen, 2003; Cappelli et al., 2023; Gurgula, 2020). As a result, patents may better capture a firm's technological mix than its technological strength (Reeb & Zhao, 2020). Cosine similarity captures this compositional element while abstracting away from differences in patent volumes.

In addition, to control for the acquirer's observable technological position relative to the industry frontier, I construct an *Alignment* score as the cosine similarity between the acquirer's patent vector $\mathbf{P}_{it}^{Acq}$ and its industry frontier $\mathbf{P}_{it}^{AInd}$:

$$Alignment_{it} = \frac{\mathbf{P}_{it}^{Acq} \cdot \mathbf{P}_{it}^{AInd}}{\|\mathbf{P}_{it}^{Acq}\| \cdot \|\mathbf{P}_{it}^{AInd}\|}. \tag{25}$$

This score reflects the extent to which the acquirer's technology aligns with the technological frontier of its industry. Higher values indicate better alignment, while lower values suggest a technological gap. *Alignment* captures public information observable prior to the acquisition announcement. In contrast, *GapSignal* captures information specific to the acquirer-target match and becomes available only upon the acquisition announcement.

3.2.3 Other variables

Cumulative abnormal returns (CARs). The main dependent variable in this paper is CARs around acquisition announcement dates. I compute CARs for both acquirers and targets using the four-factor model of Fama and French (1993) and Carhart (1997). The model is estimated over a 200-trading day estimation window that ends 20 trading days prior to the announcement to avoid event contamination. CARs are calculated over two symmetric event windows: $[-1, 1]$ and $[-3, 3]$, where day 0 is the announcement date, or the immediate trading day after it.

Corporate opacity measures. To empirically examine the moderating role played by acquirer and target opacity as theorized in Section 2.2.3, I employ two widely adopted proxies for firm-level opacity: bid-ask spreads and analyst following.[7] I follow Abdi and Ranaldo

[7] For example, Anderson, Duru, and Reeb (2009) combine both proxies into a composite opacity index. Daske et al. (2008), Cheng, Courtenay, and Krishnamurti (2006), and Leuz and Verrecchia (2000) show that improved disclosure reduces bid-ask spreads. Hong, Lim, and Stein (2000) find that analyst following accelerates information diffusion.

(2017) to estimate effective bid-ask spreads using closing, high, and low prices, as closing bid-ask quotes reported by CRSP do not fully span my sample period. Analyst following is measured as the number of analysts providing earnings forecasts for a firm within a given calendar year, based on I/B/E/S data.

Firm-level control variables. For each pair of acquirer and target, I construct the following variables for both firms: total assets, patent stock, Tobin's Q, and market leverage. These variables capture, respectively, firm size, historical patenting activity, market valuation, and financial condition. The first three firm-level controls are measured in logarithmic form. All four controls are based on the most recent fiscal year preceding the acquisition announcement. Detailed definitions are provided in Table A2.

Deal-level control variables. I characterize each acquisition using the following dimensions: the percentage of the transaction paid in cash (*% in cash*); whether the deal is structured as a tender offer (*Tender offer*); whether the acquisition is hostile (*Hostile*); the presence of competing bids (*Competitive*); the acquirer's toehold, i.e., pre-existing ownership stake in the target (*Toehold*); whether the deal is cross-border (*Cross-border*); whether the acquirer and target operate in the same industry (*Horizontal*) or are product market rivals (*Prod. market rival*), based on the classification by Hoberg and Phillips (2010); and whether the deal was preceded by public rumors (*Rumored deal*). These variables help account for deal structure, strategic complexity, and competitive environment, all of which may influence market reactions independent of technological considerations. Detailed definitions are provided in Table A2.

3.3 Descriptive statistics

Figure 3 breaks down the sample by year. Panel A shows the annual distribution of acquisitions in the sample from 1990 to 2020, separated by the target's listing status. The volume of technology-oriented acquisitions rises sharply during the late 1990s and early 2000s, coinciding with the dot-com bubble, and shows another uptick in the mid-2010s, potentially reflecting renewed interest in digital transformation and platform-based business models.

Panel B displays the average acquirer CARs over two symmetric event windows: CAR(-1,1) and CAR(-3,3). Acquirer returns around public-target announcements are often, on average, negative over the sample period, whereas private-target acquisitions are almost consistently associated with positive acquirer returns. This divergence is persistent across time and event windows.

Panel C plots the average *GapSignal* score by year. While both public- and private-target deals show an upward trend, the average *GapSignal* is consistently higher for public-target acquisitions, suggesting that public targets tend to be more technologically aligned with the technological frontier of the acquirer's industry.

Table 1 presents summary statistics for the sample of acquisitions, separated by whether the target is a public or private firm. Panel A reports acquirer characteristics. Consistent with prior literature and the time-series pattern shown in Figure 3, acquirers of public targets experience significantly negative announcement CARs (mean CAR(-1,1) = –1.2%, $p < 0.01$; mean CAR(-3,3) = –1.6%, $p < 0.01$), while acquirers of private targets earn significantly positive CARs (mean CAR(-1,1) = 2.3%, $p < 0.01$; mean CAR(-3,3) = 1.7%, $p < 0.01$). Public-target acquirers are substantially larger, hold larger patent portfolios, and have slightly higher market leverage. All differences are statistically significant at the 1% level.

Panel B compares target characteristics. In line with established findings, target firms experience large positive announcement returns (mean CAR(-1,1) = 24.9%, $p < 0.01$; mean CAR(-3,3) = 25.5%, $p < 0.01$). Public targets are significantly larger and more patent-intensive than private targets, with all differences highly significant.

Panel C summarizes deal-level features. Public-target acquisitions exhibit significantly higher *GapSignal* scores, consistent with Figure 3. By contrast, the *Alignment* score, which measures the acquirer's own proximity to the frontier, does not differ significantly between the two groups. Public-target deals are also more likely to be structured as tender offers, hostile, cross-border, or rumored, whereas private-target acquisitions are more likely to result in deal completion. All these differences are statistically significant. Finally, public-target acquisitions involve significantly higher cash consideration, which may reflect acquirers' stronger bargaining position when negotiating with private firms.

Lastly, the sample acquirers are concentrated in a few technology-intensive industries. The five most represented industries are business services (SIC 73; 17.6%), precision equipment (SIC 38; 16.4%), chemicals (SIC 28; 14.9%), electronics (SIC 36; 14.7%), and machinery (SIC 35; 11.2%). Together, these sectors account for approximately 75% of the sample. The remaining acquirers are distributed across other manufacturing industries (11.8%) and service sectors (13.6%). This distribution underscores the sample's strong orientation toward R&D- and innovation-driven firms.

4 Analysis

4.1 Technological gaps and acquirer revaluation

Figure 4 sorts public- and private-target acquisitions into terciles based on the *GapSignal* score and reports the average acquirer CARs within each tercile for two event windows: CAR(-1,1) and CAR(-3,3). Among public-target acquisitions (Panel A), a clear negative relationship emerges between *GapSignal* and acquirer returns, consistent with Hypothesis 1. This pattern suggests that when a public target more closely resembles the acquirer's technological frontier, the market interprets the deal as revealing a larger technological gap for the acquirer, prompting negative revaluation. Among private-target acquisitions (Panel B), a similar negative association is also evident, although average CARs remain positive across all terciles.

Next, I formally test the relationship between acquirer returns and the revealed technological gap by estimating the following regression model:

$$CAR(-\tau,\tau)_{id} = \gamma \cdot GapSignal_d + \mathbf{X}_{id} \cdot \mathbf{\Gamma} + \alpha_u + \alpha_v + \alpha_t + \varepsilon_{id}, \tag{26}$$

where i indexes acquirers, d indexes acquisition deals, u and v denote 2-digit SIC industry of the acquirer and the target, respectively, and t represents the calendar year. $\mathbf{X}_{id}$ is a vector of control variables capturing firm- and deal-level characteristics, as introduced in Section 3.2.3. The regression includes industry and year fixed effects α_u, α_v, α_t to account for unobserved heterogeneity across industries and time. The coefficient of interest, γ, captures the marginal effect of the revealed technological gap, proxied by *GapSignal*, on the acquirer's abnormal return.

4.1.1 Acquirers of public targets

I start with the sample of acquirers of public targets. Table 2 reports the regression results based on Equation (33), using public-target acquirer's CAR(-1,1) as the dependent variable in Panel A, while CAR(-3,3) in Panel B.

Across all specifications in both panels, the coefficient on *GapSignal* is negative and statistically significant at the 1% level, except in Column (3) Panel A, where it remains significant at the 5% level. This result supports the baseline hypothesis: when a target's technological profile more closely resembles the acquirer's industry frontier, the market interprets the acquisition as revealing a larger underlying technological gap in the acquirer, triggering a negative revaluation.

Notably, the more stringent fixed effects introduced in Columns (4) and (5) of both panels strengthen the estimated relationship. Column (4) controls for time-varying factors specific to either the acquirer's or the target's industry by including acquirer-year and target-year fixed effects. Column (5) further saturates the specification by controlling for time-varying factors at the acquirer-target industry-pair level. Importantly, these saturated fixed effects do not weaken the coefficient on *GapSignal*; rather, they amplify it substantially. Relative to Columns (1)–(3), the coefficient magnitude roughly doubles in Panel A and increases by over 50% in Panel B. This pattern suggests that the fixed effects absorb considerable noise and mitigate attenuation bias, thereby sharpening the estimated effect of the revealed technological gap on acquirer returns.

The magnitude of the effect is also economically meaningful. A one-standard deviation increase in *GapSignal* is associated with a 0.83–1.79 percentage point decline in CAR(-1,1) and a 1.23–1.83 percentage point decline in CAR(-3,3). These changes represent approximately 10–21% of the standard deviation of the respective CARs.

Control variables. The effect of *Alignment*, which captures the acquirer's own proximity to the technological frontier, is negative but statistically significant only in Column (2) of Panel A. The effect becomes insignificant once firm-level controls are introduced in Column (3), suggesting that the market has already priced in the acquirer's observable technological orientation prior to the acquisition announcement.

A higher share of cash payment (*% in cash*) is consistently associated with more positive announcement returns. This finding aligns with prior literature, which interprets cash financing as a signal of acquirer undervaluation. The economic magnitude is comparable to—even slightly smaller than—that of *GapSignal*: a one-standard deviation increase in the cash share corresponds to an 8–16% standard deviation increase in CARs. This underscores the strong explanatory power of the informational mechanism captured by *GapSignal*.

Additionally, larger acquirers tend to earn significantly higher announcement returns, whereas acquisitions of larger targets are associated with lower acquirer returns, consistent with established findings in the literature.[8] This pattern may reflect relative bargaining power in negotiations or the greater complexity and integration costs associated with acquiring large targets. Other untabulated control variables do not exhibit consistent or robust effects across specifications.

Overall, these results reaffirm the visual pattern observed in Figure 4, Panel A, and provide strong empirical support for Hypothesis 1.

4.1.2 Acquirers of private targets

Table 3 presents regression results using the same specification as in Table 2, but based on the sample of private-target acquisitions.[9]

In contrast to the results for public-target acquirers, the coefficient on *GapSignal* is

[8]See, for example, Loderer and Martin (1990) and Moeller, Schlingemann, and Stulz (2004).

[9]Note that some independent variables are not available for private-target acquisitions, including target *Tobin's Q*, target *Market leverage*, and *Prod. market rival*—the indicator for whether the acquirer and the target are product market rivals, since Hoberg and Phillips (2010) only classify product markets for public companies. Additionally, *Competitive* is also excluded because none of the sample private-target acquisitions are subject to competitive bidding.

statistically indistinguishable from zero across all specifications in both panels. This finding stands in contrast to the suggestive pattern in Figure 4, Panel B, and indicates that the market does not systematically revalue acquirers of private targets based on the technological profile of the latter.

While initially puzzling, this finding is not necessarily inconsistent with the revaluation mechanism. As shown theoretically in Section 2.2.3, the intensity of market revaluation depends critically on the informativeness of the target relative to the acquirer. When the target is more opaque—meaning that the signal it provides about the acquirer's technological position is noisier than the acquirer's own observable characteristics—the revaluation effect can be substantially weakened, or even fully muted in the case of perfectly correlated noise components.

In the context of private-target acquisitions, this condition is likely to hold. First, private firms are not subject to the same regulatory disclosure requirements as their publicly traded counterparts, making them inherently less transparent. Second, as reported in Table 1, private targets in the sample are, on average, less than one-fifteenth the size of their acquirers, and smaller than one-thirtieth the size of public targets. These stark differences in size suggest that private targets are substantially more opaque, which limits the market's ability to draw inferences about the acquirer based on the target's technological profile. As a result, the revaluation effect might be weakened or absent following acquisitions of private firms.

Control variables. The effect of *Alignment* is negative but statistically significant only in Columns (2) and (3) in both panels. Its effect becomes insignificant once time-varying industry heterogeneity is controlled for in Columns (4) and (5), echoing the similar pattern in Table 2.

Interestingly, relative to Table 2, the coefficients on *% in cash* in both panels and acquirer *Log asset* in Panel A reverse in sign, while all other coefficients lose statistical significance and fluctuate around zero across specifications. This underscores the distinct and complex dynamics underlying private-target acquisitions. Lastly, in both panels, the adjusted R^2 in Columns (4)–(5) is substantially smaller than in Columns (1)–(3), and even turns negative in Column (4), Panel B. This reflects the fact that the granular fixed effects included in Columns (4)–(5) are oversaturated.

Next, I empirically examine how relative acquirer–target opacity moderates revaluation, and provide further insights into the muted relationship between acquirer returns and revealed technological gaps in private-target acquisitions.

4.2 The moderating role of informational frictions

This section empirically tests Hypothesis 2: a relatively more transparent target strengthens revaluation while a relatively more transparent acquirer dampens it. Due to limited data availability for private companies, analyses in this section focus on acquirers of private targets.

First, I define the acquirer–target relative opacity as a normalized measure, analogous to Equation (22), by scaling the difference in the opacity levels of the acquirer and the target, respectively, by their average magnitude:

$$\Omega = \frac{\omega^{Acq} - \omega^{Tar}}{0.5 \cdot (|\omega^{Acq}| + |\omega^{Tar}|)}, \tag{27}$$

where ω denotes a firm's opacity measure. As introduced in Section 3.2.3, I use two standard proxies for opacity: bid-ask spreads and analyst coverage. Firms with wider bid-ask spreads or fewer analysts following are considered more opaque. To ensure consistency in interpretation across proxies, I use the negative of analyst coverage as the opacity measure, so that higher values of ω uniformly indicate greater opacity.

The opacity proxies—bid-ask spreads and analyst following—indicate that 24% and 20% of acquirers, respectively, are more opaque than their targets in public-target acquisitions ($\Omega > 0$). This is not surprising, given that the average acquirer is twice the size of the average target, and the median acquirer is eight times as large as the median target in the public-target acquisition sample, according to Table 1.

To examine how the acquirer-target relative opacity Ω moderates revaluation intensity, i.e., the strength of the relationship between the acquirer's announcement returns and its revealed technological gap. I model the marginal effect of *GapSignal* on acquirer CARs as a function of Ω:

$$\frac{\partial CAR}{\partial GapSignal} = g(\Omega). \tag{28}$$

Figure 2 illustrates the shape of the function $g(\cdot)$ predicted by the model, which is generally decreasing in Ω. That is, as the acquirer becomes more opaque relative to the target, the market is more able to extract new information from the target's technological profile, amplifying the revaluation effect. Importantly, the shape of $g(\cdot)$ also depends on the correlation between the noise components in the signals derived from the acquirer and the target. As this correlation approaches unity, the function exhibits a sharper turning point near the point of equal opacity ($\Omega = 0$), reflecting an abrupt switch in the signal the market relies on—placing greater weight on the more informative source while effectively disregarding the other.

I estimate the function $g(\cdot)$ using two complementary approaches. First, to accommodate the possibility of a cusp at $\Omega = 0$, I model $g(\cdot)$ as a piecewise linear function with a breakpoint at $\Omega = 0$. Second, to allow for more flexible nonlinearity in the $g(\cdot)$, I also adopt a restricted cubic spline (RCS) specification. The RCS approach fits a piecewise cubic polynomial with continuity and smoothness constraints at the knot points, enabling the shape of $g(\cdot)$ to vary smoothly across the domain of Ω. Appendix A.4 introduces the methodology in detail.

Results. Figure 2 plots the estimated function $g(\cdot)$. Panels A and B use bid-ask spreads as the proxy for opacity, while Panels C and D use (negative) analyst following. Panels A and C estimate $g(\cdot)$ using a piecewise linear specification; Panels B and D use a RCS specification.

Across all panels, a consistent pattern emerges: as the target becomes more transparent relative to the acquirer (i.e., as Ω increases), revaluation intensifies. In other words, the marginal effect of *GapSignal* on acquirer returns becomes more negative. This is consistent with the theoretical prediction that the relationship between acquirer returns and the revealed technological gap is negative, and that this effect is amplified when the market can better extract information from the target.

Importantly, the revaluation intensity is close to zero when the target is more opaque than the acquirer (i.e., $\Omega < 0$), suggesting that the market places little weight on the target as an information source in such cases. In contrast, when the target is more transparent (i.e., $\Omega > 0$), the market interprets the target as a more credible source for inferring the acquirer's technological gap, leading to stronger revaluation.

A particularly striking feature is the sharp turning point around $\Omega = 0$, which is evident even in the RCS results (Panels B and D), despite the fact that $g(\cdot)$ is, by construction, a smooth curve. This apparent discontinuity suggests an abrupt shift in the market's reliance from one signal to the other, consistent with a high correlation in the noise components of the signals derived from the acquirer and the target. This corresponds to the theoretical case in Figure 2 where the correlation between the acquirer and target signals $\rho = 1$.

The results also suggest that the negative revaluation of the acquirer is concentrated in roughly one-quarter to one-fifth of public-target acquisitions, while the remaining acquirers experience little to no revaluation. To the extent that the coefficients on *GapSignal* in Table 2 represent the average revaluation intensity across all public-target deals, then acquirers that are more opaque than their targets ($\Omega > 0$) likely experience revaluation effects four to five times stronger than the average, while the rest ($\Omega < 0$) are largely unaffected.

Overall, these results provide strong support for Hypothesis 2 and further corroborate Hypothesis 1.

4.3 Reassessing the private-target puzzle

Having established that negative revaluation in public-target acquisitions concentrates in deals where the target is more transparent than the acquirer, the muted effect observed for private-target acquirers (Table 3) becomes less surprising. Private targets are, on average, significantly more opaque than their public acquirers, which likely limits the market's ability to make inferences based on the target's profile. As a result, the average marginal effect of *GapSignal* is too weak to detect. However, this also suggests a testable implication: if the mechanism holds, I should observe negative revaluation among private-target acquirers when the target is exceptionally transparent.

To this end, I leverage private targets that have issued corporate bonds (or other securities) prior to the acquisition announcement. Bond issuance by a private firm typically requires adherence to disclosure standards and engagement with credit markets, which enhances transparency relative to other private firms. These targets are also more likely to be tracked by institutional investors and information intermediaries, such as credit rating agencies. Accordingly, I treat bond issuance as a proxy for exceptional transparency among private firms.

I construct this transparency proxy using three complementary data sources. First, I identify corporate bond issuances by private firms using records published by the Financial Industry Regulatory Authority (FINRA), which provides direct evidence of credit market offerings. Second, I search for headlines in CapitalIQ that reference corporate bond offerings by private targets, capturing disclosures through financial media. Lastly, I incorporate information from SDC on whether a target has been assigned a SEDOL code prior to the acquisition announcement. Since SEDOL identifiers are typically allocated to firms involved in public or quasi-public securities markets, their presence signals a heightened level of financial visibility. In total, 46 private targets—representing approximately 4.9% of the private-target sample—meet these criteria and are classified as exceptionally transparent.

Next, I replicate the analyses in Table 3 while interacting *GapSignal*—the acquirer's revealed technological gap—with an indicator for transparent targets. Table 4 reports the regression results. The interaction term is negative and statistically significant across all specifications (except for Column (4) in Panel B), suggesting that acquirers of exceptionally transparent private targets experience negative revaluation when the target's technological profile closely resembles the acquirer's industry frontier.

The marginal effect of *GapSignal* on acquirer CARs in these regressions is given by the sum of the coefficients on the interaction term and *GapSignal*. This combined effect is roughly four to five times as large as the corresponding coefficient in Table 2. In other words, the revaluation intensity faced by acquirers of exceptionally transparent private targets is on par with that experienced by acquirers of public targets that are more transparent than their acquirer, as measured by bid-ask spreads and analyst following.

4.4 Disentangling prediction and surprise

The analyses thus far have implicitly assumed that *GapSignal* captures information that surprises the market. This rests on the premise that, at the time of the acquisition announcement, investors have not fully internalized the acquirer's technological gap. The observed revaluation, then, reflects a market response to newly revealed information conveyed through the acquirer's choice of target. However, this interpretation warrants further scrutiny. A large body of literature has identified a variety of observable firm characteristics—such as size, valuation, growth opportunities, and R&D intensity—that predict acquisition activity. Whether the effect documented here genuinely reflects informational surprises, or whether it simply captures dimensions already priced by the market, remains an open empirical question. Moreover, it is important to assess the extent to which the self-selection mechanism proposed in this paper complements, or overlaps with, existing theoretical frameworks. To this end, I conduct a brief review of relevant studies.

4.4.1 Acquisition antecedents

First, I consider firms' innovation input and output, drawing on Bena and Li (2014), who show that firms with big patent portfolios but low R&D intensity are more likely to become acquirers. Following their definitions, I construct four variables to characterize firms' innovative capabilities and their changes over time: $R\&D/assets$, $Patent\ index$, $\Delta R\&D/assets$, and $\Delta Patent\ index$. These capture both levels and trends in firms' innovation activities.

Second, I incorporate the insight of Phillips and Zhdanov (2013), who argue that large, mature firms tend to outsource R&D through acquisitions. To reflect this, I include measures of acquirer size and maturity: *Log asset*, *Patent stock*, and firm *Age*. These variables also indirectly speak to the view that managers of entrenched firms may use acquisitions defensively to preempt future takeovers, as argued by Gorton, Kahl, and Rosen (2009).

Third, I consider neoclassical acquisition motives. According to Jovanovic and Rousseau (2002) and Maksimovic and Phillips (2001), firms with higher productivity tend to acquire less productive ones to allocate capital more efficiently. I measure productivity via $Tobin's\ Q$ and a standard estimate of total factor productivity (TFP), assuming a Cobb-Douglas production function with capital and labor inputs. Notably, $Tobin's\ Q$ also reflects valuation-driven motives, as emphasized in Dong et al. (2006), Rhodes-Kropf, Robinson, and Viswanathan (2005), and Shleifer and Vishny (2003).

Fourth, I account for agency-based motives. Jensen (1986) theorizes that managers may undertake acquisitions to dissipate excess free cash flows rather than return them to shareholders. Harford (1999) provide empirical support for this claim. To capture this perspective, I include measures of financial slack: $Cashflow/asset$, $Cash/asset$, and $Market\ leverage$. These variables also reflect the enabling role of liquidity in driving acquisition waves, as documented by Harford (2005).

Fifth, I consider internal investment opportunities as a motive. According to Levine (2017), firms may pursue acquisitions when they lack investment opportunities internally. I include *Capex/asset* and *Sales growth* to capture this logic, reflecting the firm's investment intensity and growth perspective.

Sixth, competition may pressure firms to acquire external innovation or suppress rivals. Higgins and Rodriguez (2006) document that pharmaceutical firms use acquisitions to renew their innovation pipelines in the face of patent expirations. Cunningham, Ederer, and Ma (2021) find that firms engage in "killer acquisitions" to preempt emerging competitors. To reflect industry conditions, I use two Herfindahl indices: one based on product-market sales (*Competition*), and the other based on patent stock (*Tech competition*). Both are transformed as one minus the standard Herfindahl index, so that higher values reflect greater competition.

Lastly, I incorporate measures of managerial overconfidence, in line with the hubris hypothesis of Roll (1986) and further developed by Malmendier, Opp, and Saidi (2016). Following Barber and Odean (2001) and Huang and Kisgen (2013), I use the presence of a female executive (*Female executive*) or a female CEO (*Female CEO*) as inverse proxies for overconfidence based on robust evidence that male managers are, on average, more overconfident in financial decision-making.

4.4.2 Decomposing the gap measure

To investigate whether the effect of *GapSignal* is truly driven by informational surprises, I examine to what extent it can be explained by firm characteristics previously identified as acquisition antecedents. To that end, I estimate the following regression model:

$$GapSignal_{id} = \mathbf{Z}_{id} \cdot \mathbf{\Xi} + \alpha_u + \alpha_v + \alpha_t + \varepsilon_{id}, \tag{29}$$

where i indexes acquirers, d indexes acquisition deals, u and v denote 2-digit SIC industry of the acquirer and the target, respectively, and t represents the calendar year. $\mathbf{Z}_{id}$ is a vector of acquisition antecedents, as listed in Section 4.4.1. The regression includes industry and year fixed effects α_u, α_v, α_t to account for unobserved heterogeneity across industries and time.

I estimate the model using the sample of public-target acquisitions, since private targets, on average, reveal little information about the acquirer's technological position. Table 5 presents the results.

Column (1) shows that higher R&D intensity is strongly associated with higher *GapSignal* scores, while increases in R&D intensity predict lower scores, suggesting that gap bidders' acquisition motives are distinct from those documented by Bena and Li (2014). Rather, gap bidders tend to be R&D-intensive companies facing a decline in R&D investment—probably due to a lack of internal growth opportunities. Columns (2) indicates that larger and younger acquirers have higher *GapSignal* scores, only partially consistent with theories of strategic outsourcing. Column (3) demonstrates that more productive acquirers are more frequently gap bidders, suggesting that gap bidders' acquisition motives overlap with those predicted by neoclassical acquisition theories. In Column (4), market leverage is negatively associated with *GapSignal*, suggesting financial constraints dampen gap-closing acquisitions.

Column (6) shows that acquirers in more competitive product markets are less likely to become gap bidders, contrary to strategic pressure arguments, but more in line with a Schumpetarian growth theory where product market competition erodes the monopolistic rents accruing to successful innovators, hence making cutting-edge technology less attractive (Aghion & Howitt, 1992). Column (7) finds no significant effect of managerial gender traits. Column (8) further rules out cash flow-driven agency motives and indicates that firms with weaker growth prospects are more inclined to close technological gaps via acquisition. Overall, while observable predictors explain some variation in *GapSignal*, a substantial portion remains unexplained.

Equation (29) enables a decomposition of *GapSignal* into two parts: a fitted component explained by known acquisition predictors, and a residual component orthogonal to them. Table 5 replaces *GapSignal* with these two components and re-estimates Equation (33). The results reveal that only the residual component significantly predicts acquirer CARs, suggesting that market reactions are primarily driven by the unanticipated part of the technological gap—i.e., information not already embedded in known firm and industry fundamentals.

5 Extensions and robustness

5.1 Alternative explanations

This section considers three alternative explanations for the observed negative correlation between acquirer returns and *GapSignal*, which proxies for the acquirer's revealed technological gap:

(a) overpayment for technologically advanced targets;

(b) pre-announcement anticipation, where expected gains are partially priced in, resulting in seemingly more negative reactions at the time of the announcement; and

(c) dissynergies due to technological incompatibility between the acquirer and the target.

5.1.1 Overpayment

A desperate gap bidder may overpay for a target that helps close its technological gap—especially when the gap is large and the urgency to catch up is high. This puts acquirers with larger gaps in a weaker bargaining position relative to those facing smaller gaps. If this mechanism is at play, overpayment may be misinterpreted as negative revaluation, potentially confounding the main interpretation of the market reaction.

To address this possibility, I examine the relationship between target announcement returns and *GapSignal*. The rationale is straightforward: if acquirers systematically overpay to close their technological gaps, this overpayment would constitute a wealth transfer from acquirer shareholders to target shareholders. Consequently, if overpayment were driving the results, the observed negative correlation between acquirer returns and *GapSignal* should be mirrored by a *positive* correlation between target returns and *GapSignal*.

Table 7 reports the results. Across all specifications and both event windows, the coefficient on *GapSignal* is statistically insignificant and consistently close to zero. If anything, the point estimates are negative, opposite to what the overpayment hypothesis would predict. This finding suggests that the acquirer's revealed technological gap does not predict target returns, providing no evidence that acquirers systematically overpay in gap-closing acquisitions.

Control variables. Several controls merit attention. First, *Alignment*—which captures the acquirer's proximity to the technological frontier—is negatively associated with target CARs, indicating that better-positioned acquirers may enjoy greater bargaining power. Second, the indicator for tender offers is positively and significantly associated with target returns, consistent with prior findings that unsolicited bids often carry higher acquisition premiums (Bradley, Desai, & Kim, 1988; Walkling, 1985). Finally, target size (*Log asset (T)*) is positively related to announcement returns, possibly reflecting the stronger negotiation leverage of larger targets.

5.1.2 Anticipation

Prior research shows that market anticipation can partially incorporate expected acquisition gains into stock prices before deal announcements, thereby dampening the observed acquirer returns at the time of the announcement (Cai, Song, & Walkling, 2011; Tunyi, 2021). If

GapSignal also correlates with the extent to which the market expects a firm to pursue a gap-closing acquisition, then acquirers with higher *GapSignal* values may exhibit lower announcement returns—not due to the revelation of new information, but because a greater portion of the expected gains has already been priced in.

To address this alternative explanation, I argue that pre-announcement anticipation tends to reduce the element of surprise at acquisition announcements. The greater the anticipation, the smaller the informational shock, and consequently, the more muted the market reaction. Therefore, if *GapSignal* primarily captures market anticipation rather than new information, a higher *GapSignal* should be associated with a smaller absolute magnitude of CARs, regardless of direction.

In this light, I regress the absolute value of acquirer CARs against *GapSignal*. Table 8 presents the results. Panel A reports the results for the event window CAR(-1,1), and Panel B for CAR(-3,3). Columns (1) and (2) reveal a positive and statistically significant relationship between *GapSignal* and |CAR| If *GapSignal* merely captured pre-announcement anticipation, I would expect to see smaller absolute returns as *GapSignal* increases, reflecting muted surprise. Instead, the results suggest that larger revealed technological gaps lead to stronger market reactions, which is inconsistent with the prediction of an anticipation-based explanation.

Columns (3) through (6) split the sample based on whether CARs are negative or non-negative. The negative relationship between *GapSignal* and acquirer returns is concentrated entirely among deals with negative acquirer CARs—those that likely triggered the strongest negative revaluation. In contrast, *GapSignal* has no meaningful effect when CARs are non-negative, suggesting that revaluation is largely absent in those cases.

In summary, the negative relationship between *GapSignal* and acquirer returns is unlikely driven by market anticipation.

5.1.3 (Dis)synergies

GapSignal measures the similarity between the target's technological portfolio and that of the acquirer's industry peers. A natural alternative interpretation, then, is that high *GapSignal* reflects an acquirer's tendency to imitate the technological direction of its peers—potentially to its own detriment. In this view, the measure may capture strategic misalignment or inefficiency arising from blind conformity, where the acquirer pursues targets without critically assessing whether the target is compatible with its own capabilities or long-term strategy. Under this hypothesis, the negative correlation between acquirer CARs and *GapSignal* reflects growing dissynergies arising from a widening mismatch between the acquirer and the target.

However, I argue that it is unlikely that *GapSignal* systematically captures dissynergies. As documented in Section 4.2, the marginal effect of *GapSignal* on acquirer CARs is moderated by the relative opacity between the acquirer and the target: acquirers that are more opaque than their targets tend to experience stronger negative revaluation. This is conceptually at odds with a dissynergy-based explanation, which would require clarity and transparency to identify potential mismatches. In other words, if dissynergies were the primary driver, the effect of *GapSignal* should weaken when the acquirer is more opaque, contrary to what my evidence suggests.

That said, potential synergies may bias the estimated scale of revaluation triggered by the acquirer's revealed technological gap. Specifically, while the target's technological profile may expose a deficiency in the acquirer, it may also simultaneously reveal unexpected complementarities—sources of synergy that would not have existed without the gap. In such cases, the positive valuation effects of synergies could offset the negative effects of revaluation, biasing the estimated impact toward zero. As a result, the observed negative relationship between *GapSignal* and acquirer returns should be interpreted as an upper bound on the true revaluation effect, or equivalently, a lower bound on its magnitude.

5.2 Redefining the gap measure

The earlier analyses define *GapSignal*—the alignment between the target's technological profile and the acquirer's technological frontier—using 137 technological classes derived from the *class* level of the CPC classification system. To ensure that the main results are not sensitive to the granularity of the classification scheme, I re-estimate *GapSignal* based on the more detailed *subclass* level, which includes 680 categories.

With the redefined *GapSignal*—constructed using CPC subclass codes—I replicate the baseline analysis from Table 2. Table 9 presents the results. The estimates are both qualitatively and quantitatively similar to the baseline, confirming that the negative relationship between *GapSignal* and acquirer announcement returns is robust to alternative definitions of the revealed technological gap. In both event windows—CAR(-1,1) and CAR(-3,3)—the coefficients on *GapSignal* remain negative and statistically significant across all specifications. However, the results in Panel A show somewhat weaker statistical significance in Columns (1)–(3). This attenuation likely arises from the assumption implicit in cosine similarity that all dimensions are mutually orthogonal, even though the technological distance between patent categories may vary. As the classification scheme becomes more granular, this assumption introduces greater measurement noise, potentially weakening the informativeness of the signal extracted from the target's patent portfolio. Nonetheless, the overall findings remain consistent and robust.

5.3 Are targets revalued?

Thus far, this paper has demonstrated that an acquirer's choice of target can reveal the acquirer's weaknesses and trigger negative revaluation. A natural question that follows is whether the reverse inference is also possible: can the market infer hidden characteristics of the target firm based on observable features of the acquirer?

The M&A market is increasingly understood through the lens of two-sided matching frameworks.[10] In such models, the formation of acquirer–target pairs reflects the preferences of both parties, suggesting that observed matches embed information about the underlying—potentially hidden—characteristics that shape these preferences. Supporting this perspective, Wang (2018) find that revaluation effects explain approximately 26% of the variation in target announcement returns. Notably, however, the share is substantially higher on the acquirer side, where revaluation accounts for 58% of the return variation. This asymmetry suggests that, while target characteristics matter, observed deal outcomes are more strongly shaped by the acquirer's preferences and informational content, likely due to their larger size and greater bargaining power.

To empirically examine whether partnering with an acquirer that helps the target close its technological gap leads to negative revaluation of the target, I construct target-side analogs of the *GapSignal* and *Alignment* measures. Specifically, *GapSignal (T)* captures the alignment between the acquirer's technological profile and the target's industry technological frontier, reflecting the extent to which the acquirer helps fill the target's technological gap. *Alignment (T)*, by contrast, measures the similarity between the target's own technological portfolio and the frontier of its industry, capturing the target's standalone technological positioning.

Table 10 reports the results. In the baseline models—Columns (1) and (4)—target *GapSignal* is negatively associated with target CARs, with significance at the 5% and 10% levels, respectively. However, once more stringent fixed effects are introduced, the statistical significance dissipates, suggesting that the effect is not particularly robust. The other tabulated variables are uniformly insignificant across specifications. Taken together, the results provide only suggestive evidence that targets are revalued downward when the deal implies that the acquirer is filling a technological gap for the target. However, this effect—if present—is considerably weaker and less systematic than the revaluation observed on the acquirer side.

[10] See, for example, Akkus, Cookson, and Hortaçsu (2016) and Fox (2018).

6 Conclusion

This paper reframes how we interpret market reactions to acquisition announcements by emphasizing that deals can systematically reveal hidden weaknesses about the acquirer. Acquirers with disadvantages—such as technological deficiencies examined in this study—may self-select into acquisitions as a means of closing competitive gaps, making the act of acquisition itself informative about the acquirer's disadvantageous competitive standing. Specifically, in technology-oriented acquisitions, a target's technological profile serves as a signal: when the target closely resembles the technological frontier of the acquirer's industry, the market infers that the acquirer is lagging behind, triggering negative revaluation.

The strength of this revaluation, however, depends on the degree of informational frictions. When the target is more opaque than the acquirer—as is typically the case with private targets—the market cannot extract reliable inferences based on the target's observable traits, and the revaluation effect is muted. This asymmetry offers a novel explanation for the longstanding puzzle that acquirers of private targets tend to earn positive announcement returns: not because the deals are better, but because they reveal less negative information. More broadly, these findings underscore the importance of informational dynamics—alongside deal fundamentals—in shaping M&A outcomes.

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A Appendix

A.1 Name matching

I establish record linkage between the universe of USTPO patent assignees and the universe of CapitalIQ companies.

First, I standardize all assignee and firm names and apply a frequency-based name matching algorithm following Hall, Jaffe, and Trajtenberg (2001).[11] For a second step, to improve matching quality while minimizing data losses, I require assignee-company pairs matched by the algorithm with non-identical standardized names to have a normalized Levenshtein distance of at least 0.5. All pairs below the threshold are excluded. The normalized Levenshtein distance is defined as the Levenshtein distance between two strings divided by the string length of the longer component. I further require each matched CapitalIQ firm to be assigned at least one patent within its sample period.

A.2 Construction precedures of the acquisition sample

Table A1: Sample construction. This table details the sample selection process and reports the number and percentage of observations remaining at each step. Public-target and private-target acquisitions are reported separately.

		Public-target		Private-target	
Step	Description	#	%	#	%
1	All transaction with a public acquirer and a public or private target announced in 1990-2020 and classified as "Acq. of assets," "Acq. Part. Int.," or "Acq. Maj. Int." from SDC via WRDS, with all public companies linked to CRSP and COMPUSTAT.	7,049	100.0%	19,586	100.0%
2	Keep deals where the acquirer seeks to purchase and own more than 50% of the target's shares after the acquisition.	5,605	79.5%	13,497	68.9%
3	Drop deals classified as recapitalization, repurchase or divestiture, and those with acquirers classified as an SPV.	5,413	76.8%	13,293	67.9%
4	Drop deals announced by the same acquirer within a one-month window of each other.	4,938	70.1%	11,397	58.2%
5	Merge all sample firms with patent data and all public firms with financial information. Exclude acquisitions with missing variables of interest, as well as those where the target firm has no patent records.	1,044	14.8%	962	4.9%

[11] The name standardization routine and the name matching algorithm can be downloaded under the following link: https://sites.google.com/site/patentdataproject/Home.

A.3 Variable definitions

Table A2: Variable definitions. This table defines the main variables used in this paper. All other variables are defined in the respective captions of the tables using them.

Variable	Definition	Data source
CAR(-1,1)	Cumulative abnormal returns for acquirer or targets from day -1 to day 1, with day 0 being the date of the acquisition announcement. See Section 3.2.3.	CRSP, SDC
CAR(-3,3)	Cumulative abnormal returns for acquirer or targets from day -3 to day 3, with day 0 being the date of the acquisition announcement. See Section 3.2.3.	CRSP, SDC
Total asset	Total book asset of a company. For private targets, this variable is imputed with SDC data in the following order: target asset, enterprise value, and ranking value.	COMPUSTAT, SDC
Log asset	Log-transformed total asset.	COMPUSTAT, SDC
Patent stock	The number of granted patents filed by a company in the past ten years.	USTPO
Log patent stock	Log-transformed patent stock.	USTPO
Tobin's Q	(Market capitalization + total asset - book equity) / total asset	COMPUSTAT
Log Tobin's Q	Log-transformed Tobin's Q.	COMPUSTAT
Market leverage	(Long-term debt + Long-term debt due within a year) / (Market capitalization + total asset - book equity)	COMPUSTAT
GapSignal	A measure for the acquirer's revealed technological gap. See Section 3.2.2.	USTPO, CapitalIQ
Alignment	A measure for the acquirer's technological alignment with its industry peers. See Section 3.2.2.	USTPO, CapitalIQ
% in cash	The percentage of the acquisition payment made in cash.	SDC
Tender offer	An indicator for whether an acquisition is a tender offer.	SDC
Hostile	An indicator for whether an acquisition is hostile.	SDC
Competitive	An indicator for whether an acquisition is subject to competitive bidding.	SDC
Toehold	The acquirer's ownership percentage in the target firm prior to the acquisition announcement.	SDC
Cross-border	An indicator for whether an acquisition involves two firms with residence in different countries.	SDC
Horizontal	An indicator for whether an acquisition involves two firms in the same 2-digit SIC industry.	SDC
Rumored deal	An indicator for whether an acquisition was rumored before the official announcement.	SDC
Prod. market rival	An indicator for whether an acquisition involves two firm in the same product market, as defined by Hoberg and Phillips (2010).	Hoberg and Phillips Data Library
Bid-ask spread	The annual effective bid-ask spread as defined by Abdi and Ranaldo (2017).	CRSP
Analyst following	The number of analysts following a company over a year.	I/B/E/S

Table A2: Variable definitions (continued).

Variable	Definition	Data source
Transparent target	An indicator equal to 1 if a private target is regarded as exceptionally transparent, and 0 otherwise. A private target is regarded as transparent if it meets all of the following conditions: (a) it has been assigned a SEDOL code prior to the announcement date; (b) it is recorded as having issued a corporate bond in FINRA data; and (c) CapitalIQ headlines document the bond issuance.	SDC, FINRA, CapitalIQ
R&D/asset	R&D expenses / total asset.	COMPUSTAT
ΔR&D/asset	Year-over-year change in R&D/asset.	COMPUSTAT
Patent index	An index reflecting a firm's technological standing, as defined by Bena and Li (2014).	USTPO
ΔPatent index	Year-over-year change in patent index.	USTPO
Age	The number of years since the company first appeared in the COMPUSTAT database.	COMPUSTAT
Productivity	Total factor productivity, estimated as the residual from regressing log-transformed sales against log-transformed PP&E and log-transformed employee count over 10-year rolling windows for each 2-digit SIC industry.	COMPUSTAT
Cash flow/asset	Net cashflow from operating activities / year-beginning total asset.	COMPUSTAT
Cash/asset	Cash holdings / total asset.	COMPUSTAT
Capex/asset	Capital expenditure / total asset.	COMPUSTAT
Sales growth	Year-over-year change in sales scaled by the average sales over the two years.	COMPUSTAT
Competition	One minus the Herfindahl index of sales across firms within the same 2-digit SIC industry.	COMPUSTAT
Tech competition	One minus the Herfindahl index of patent stock across firms within the same 2-digit SIC industry.	USTPO
Female executive	An indicator for whether a company has a female executive.	Execucomp
Female CEO	An indicator for whether a company has a female CEO.	Execucomp

A.4 Revaluation intensity and relative opacity

This appendix presents the estimation strategies for the function $g(\cdot)$, which captures how relative acquirer–target opacity moderates revaluation intensity—that is, the marginal effect of the acquirer's revealed technological gap on its announcement returns. See Section 4.2 for more details. For a theoretical discussion motivating this relationship, see Section 2.2.3.

The first specification models $g(\cdot)$ as a piecewise linear function that allows for a potential cusp at $\Omega = 0$. This is defined as:

$$g(\Omega) = \delta_0 + \delta_1 \Omega + \delta_2 (\Omega)_+, \tag{30}$$

where $(\cdot)_+$ denotes the positive-part operator, which equals the input if positive and zero otherwise. This specification allows for a discrete change in slope at $\Omega = 0$.

The second specification models $g(\cdot)$ using a restricted cubic spline (RCS), which provides a smooth and flexible approximation to potential nonlinearities. Following Harrell (2001). I employ a basis function approach with five knots. The k-th knot, t_k, is placed at the $100 \cdot k/(k+1)$ percentile of the distribution of Ω. The RCS representation of $g(\cdot)$ is:

$$g(\cdot) = \psi_0 + \psi_1 F_1 + \psi_2 F_2 + \psi_3 F_3 + \psi_4 F_4, \tag{31}$$

where $F_1 = \Omega$ and for $j = 1, 2, 3$:

$$F_{j+1} = (\Omega - t_j)_+^3 - \frac{t_k - t_j}{t_k - t_{k-1}}(\Omega - t_{k-1})_+^3 + \frac{t_{k-1} - t_j}{t_k - t_{k-1}}(\Omega - t_k)_+^3. \tag{32}$$

This construction ensures smoothness and continuity at the knot points and imposes linearity in the tails.

Both specifications—piecewise linear and RCS—can be expressed as linear combinations of transformed versions of Ω, denoted $\{J^s\}_{s=1}^n$, along with a constant. I estimate the following regression model:

$$\begin{aligned} CAR(-\tau, \tau)_{id} = \eta_0 \cdot GapSignal_d + \sum_{s=1}^{n} \eta_s \cdot GapSignal_d \times J_d^s + \sum_{s=1}^{n} \theta_s \cdot J_d^s \\ + \mathbf{X}_{id} \cdot \mathbf{\Gamma} + \alpha_u + \alpha_v + \alpha_t + \varepsilon_{id}, \end{aligned} \tag{33}$$

where i indexes acquirers, d indexes acquisition deals, u and v denote 2-digit SIC industry of the acquirer and the target, respectively, and t represents the calendar year. $\mathbf{X}_{id}$ is a vector of control variables capturing firm- and deal-level characteristics, as introduced in Section 3.2.3. The regression includes industry and year fixed effects α_u, α_v, α_t to account for unobserved heterogeneity across industries and time.

The model includes the transformed Ω terms $\{J_d^s\}_{s=1}^n$ and their interactions with $GapSignal$ as regressors. This specification identifies the function $g(\cdot)$ directly, since the partial derivative of the regression model with respect to $GapSignal$ yields $g(\cdot)$.

B Figures

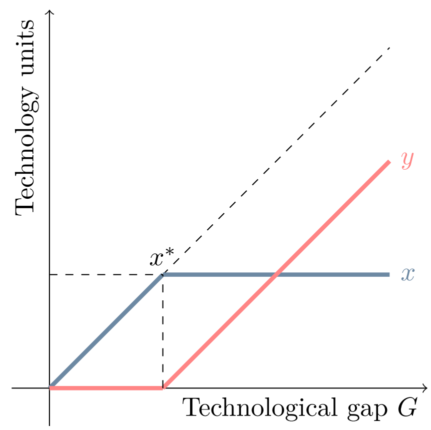


Figure 1: The pecking order of technological investment. This figure visualizes Equations (8) and (9), where the optimal in-house development x and optimal acquisition y are expressed as functions of the firm's technological gap G. x^* is the upper limit of in-house development given by Equation (4).

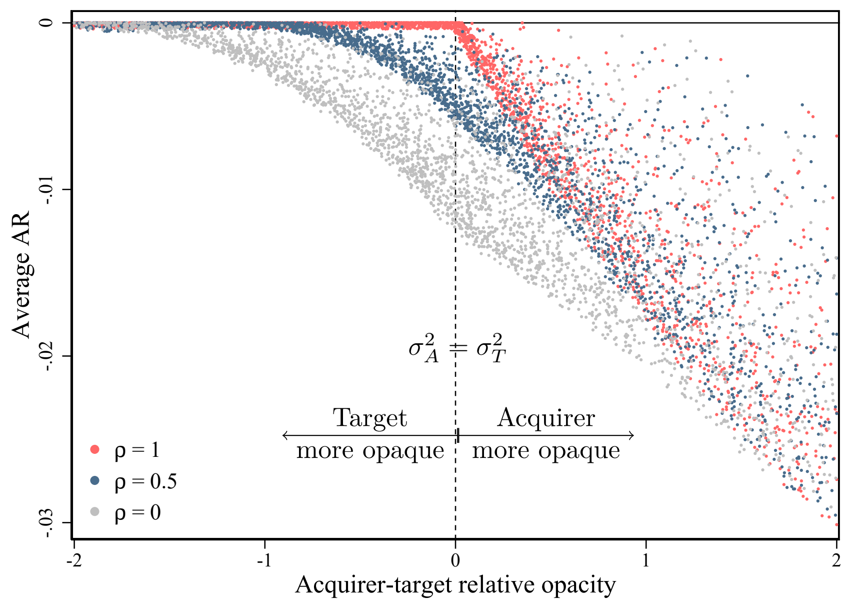
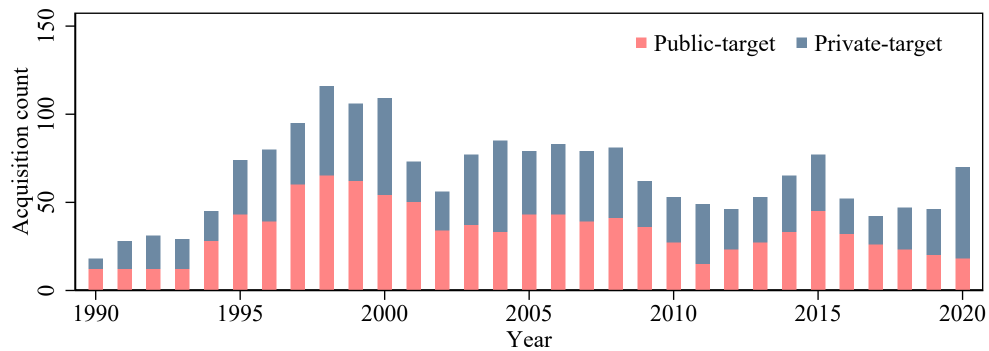
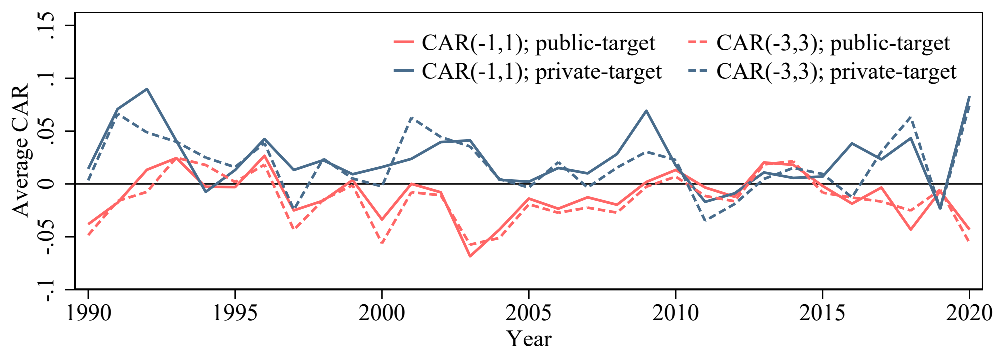


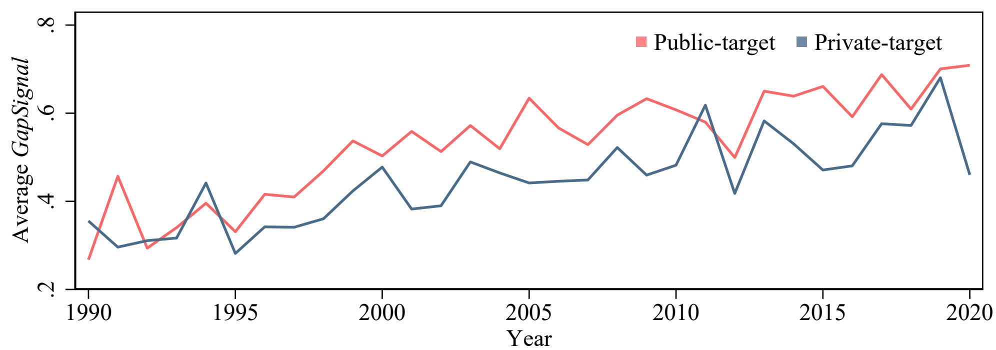
Figure 2: Revaluation intensity and relative opacity. This figure plots average ARs (Equation (21)) against relative opacity (Equation (22)) using simulated data. Each dot represents the average AR across all gap bidders in a given simulation, corresponding to a specific parameter triplet $(\sigma_A^2, \sigma_T^2, \rho)$. The signal variances are randomly drawn from a uniform distribution: $\sigma_A^2, \sigma_B^2 \sim \mathcal{U}(0, 0.05)$, while the signal correlation takes values $\rho \in \{0, 0.5, 1\}$. Other parameters are calibrated as follows: $\kappa = 1$, $\alpha = 0.25$, $p = \beta = 0.1$, $f = 0.05$, and $\phi = 2$. Notably, G is not defined beyond the interval $[0, Z]$. Therefore, the distributions of G^A and G^{AT} are truncated over $[0, Z]$ in the numerical simulations.



Panel A: Sample distribution by year

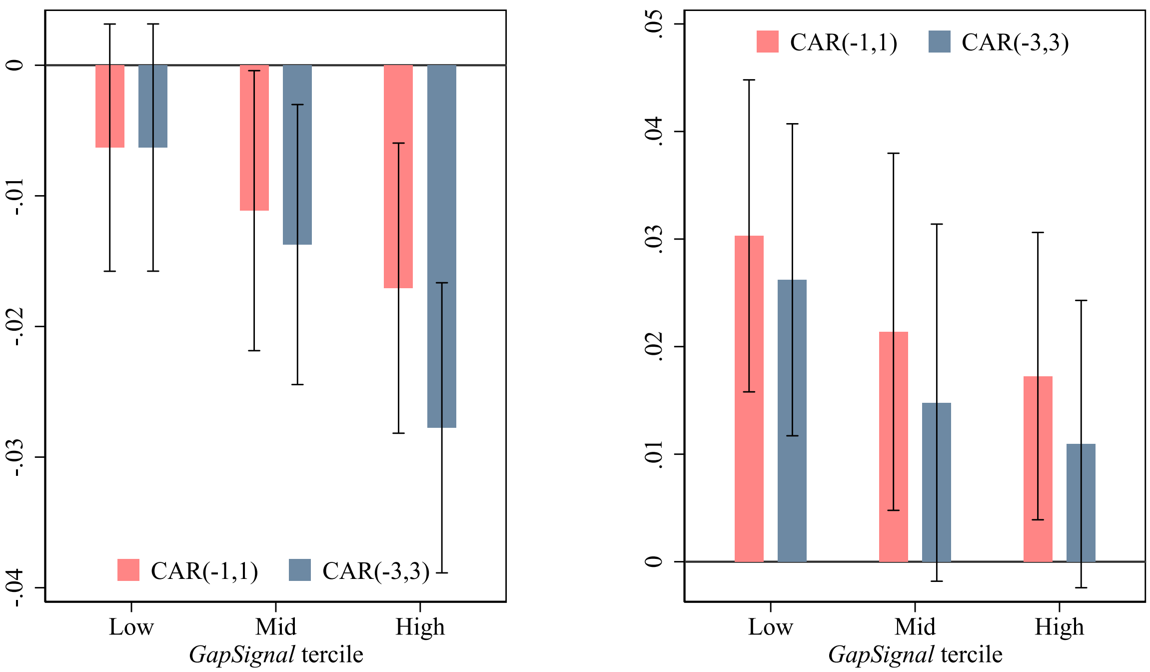


Panel B: Average acquirer CARs by year



Panel C: Average *GapSignal* by year

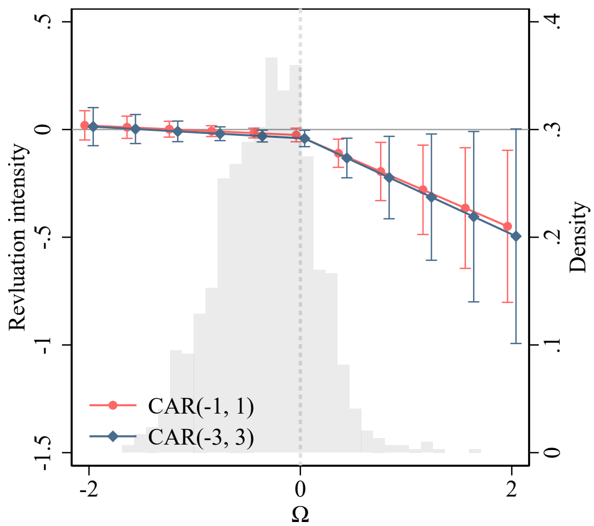
Figure 3: Acquisition sample by year. This figure summarizes the annual distribution and characteristics of the acquisition sample by the target's listing status. Panel A shows the number of public- and private-target acquisitions by year. Panel B reports average acquirer CARs over two event windows—CAR(-1,1) and CAR(-3,3)—by year and target type. Panel C presents the average *GapSignal* score by year, separately for public- and private-target acquisitions.



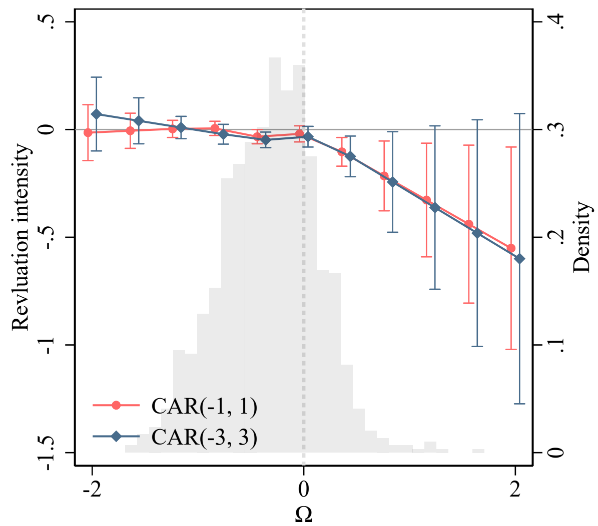
Panel A: Public-target

Panel B: Private-target

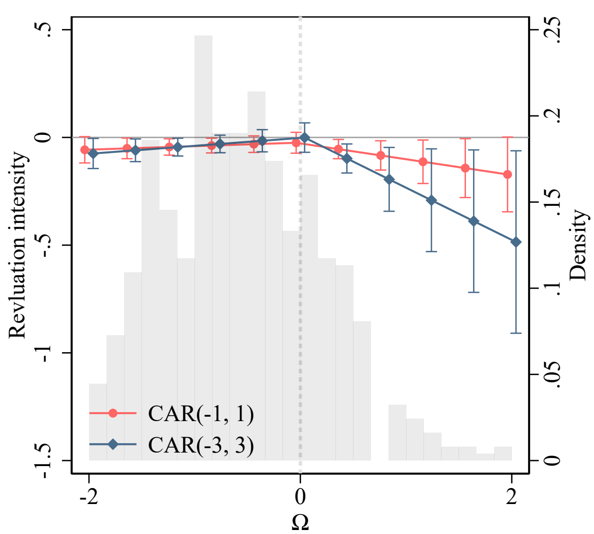
Figure 4: Revealed technological gaps and acquirer returns. This figure sorts sample acquirers of public and private targets separately into terciles by *GapSignal*, and reports the average acquirer CARs over two event windows—CAR(-1,1) and CAR(-3,3)—within each tercile, along with 95% confidence intervals.



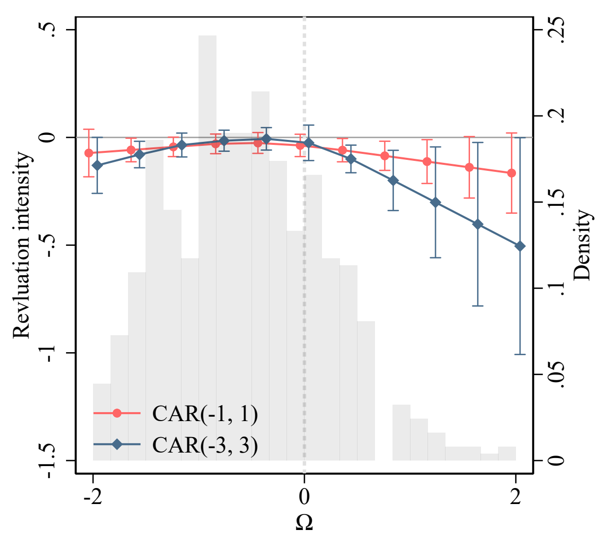
Panel A: Bid-ask spread, piecewise linear



Panel B: Bid-ask spread, RCS



Panel C: Analyst following, piecewise linear



Panel D: Analyst following, RCS

Figure 5: The moderating effect of relative opacity. This figure plots the estimated function $g(\cdot)$, as defined in Equation (28), which captures how revaluation intensity—the marginal effect of *GapSignal* on acquirer CARs—varies with acquirer–target relative opacity Ω. Panels A and B use bid-ask spreads as the proxy for opacity, while Panels C and D use (negative) analyst following. Panels A and C estimate $g(\cdot)$ using a piecewise linear specification with a breakpoint at $\Omega = 0$; Panels B and D use a RCS specification. Each panel reports point estimates of $g(\cdot)$ across selected values of Ω, along with 95% confidence intervals. The background histograms depict the distribution of Ω in the estimation sample.

C Tables

Table 1: Summary statistics. This table presents summary statistics for the full sample of acquisitions, separated by whether the target is a public or private firm. Panel A reports characteristics of the acquirers, including announcement-window cumulative abnormal returns (CARs), size, patenting activity, Tobin's Q, and market leverage. Panel B reports analogous statistics for targets. Panel C summarizes deal-level characteristics, including the *GapSignal* and *Alignment* scores, method of payment, deal type, and competitive environment. The last column reports the difference in means between public- and private-target deals. All variables are defined in Table 6.*, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Public-target (N = 1,044)			Private-target (N = 962)			Mean difference
	Mean	Median	SD	Mean	Median	SD	
Panel A: Acquirer characteristics							
CAR(-1,1)	-0.012	-0.005	0.083	0.023	0.006	0.125	-0.035***
CAR(-3,3)	-0.016	-0.010	0.099	0.017	0.007	0.136	-0.033***
Total asset ($bn)	16.418	1.706	66.826	3.738	0.343	13.393	12.680***
Log asset	7.503	7.442	2.294	5.946	5.837	2.118	1.558***
Patent stock	263.430	1.000	1,438.176	165.400	1.000	989.543	98.030**
Log patent stock	2.042	0.693	2.472	1.796	0.693	2.179	0.246***
Tobin's Q	2.765	2.037	2.374	3.049	2.098	2.719	-0.284***
Log Tobin's Q	0.798	0.711	0.610	0.858	0.741	0.677	-0.060**
Market leverage	0.107	0.075	0.115	0.076	0.027	0.103	0.030***
Panel B: Target characteristics							
CAR(-1,1)	0.249	0.187	0.315				
CAR(-3,3)	0.255	0.205	0.384				
Total asset ($bn)	7.672	0.203	82.354	0.246	0.038	1.297	7.427***
Log asset	5.632	5.311	2.141	3.723	3.646	1.822	1.909***
Patent stock	108.470	9.000	850.381	8.615	3.000	19.958	99.855***
Log patent stock	2.615	2.303	1.641	1.621	1.386	0.951	0.993***
Tobin's Q	2.429	1.713	2.245				
Log Tobin's Q	0.646	0.538	0.638				
Market leverage	0.105	0.040	0.135				
Panel C: Deal characteristics							
GapSignal	0.536	0.579	0.302	0.451	0.442	0.304	0.085***
Alignment	0.319	0.089	0.359	0.316	0.126	0.355	0.003
% in cash	0.455	0.331	0.460	0.361	0.000	0.427	0.094***
Tender offer	0.223	0.000	0.417	0.004	0.000	0.064	0.219***
Hostile	0.022	0.000	0.147	0.001	0.000	0.032	0.021***
Competitive	0.071	0.000	0.257	0.001	0.000	0.032	0.070***
Toehold	0.007	0.000	0.041	0.010	0.000	0.052	-0.003*
Cross-border	0.154	0.000	0.361	0.214	0.000	0.410	-0.060***
Horizontal	0.680	1.000	0.467	0.543	1.000	0.498	0.138***
Prod. market rival	0.563	1.000	0.496				
Rumored deal	0.127	0.000	0.334	0.013	0.000	0.111	0.115***
Completed	0.785	1.000	0.411	0.917	1.000	0.276	-0.132***

Table 2: Acquirer returns and revealed gaps with public targets. This table reports the regression results of Equation (33) based on a sample of public-target acquisitions. The dependent variables are the acquirer's CARs over two event windows: CAR(-1,1) in Panel A and CAR(-3,3) in Panel B. The main independent variable of interest is *GapSignal*, which captures the acquirer's technological gap revealed by the acquisition. Only a subset of control variables is shown for brevity; a complete list is provided in Section 3.2.3. *AInd* and *TInd* denote the 2-digit SIC industries of the acquirer and the target, respectively. All other variables are defined in Table A2. T-statistics are reported in brackets. Standard errors are robust to heteroskedasticity. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: CAR(-1,1)

Dep. var.:	CAR(-1,1) of public-target acquirers				
	(1)	(2)	(3)	(4)	(5)
GapSignal	-0.028***	-0.030***	-0.029**	-0.059***	-0.057***
	(-2.85)	(-2.73)	(-2.54)	(-3.18)	(-3.00)
Alignment		-0.016**	-0.012	-0.009	-0.004
		(-1.97)	(-0.97)	(-0.50)	(-0.21)
% in cash		0.026***	0.018**	0.029***	0.026***
		(3.84)	(2.53)	(2.87)	(2.63)
Log asset (A)			0.005**	0.009***	0.009***
			(2.47)	(3.03)	(2.94)
Log asset (T)			-0.002	-0.008**	-0.007**
			(-0.76)	(-2.19)	(-2.04)
Deal controls	No	Yes	Yes	Yes	Yes
Firm controls	No	No	Yes	Yes	Yes
Year, AInd, TInd FE	Yes	Yes	Yes	No	No
AInd × Year, Tind × Year FE	No	No	No	Yes	No
AInd × Tind × Year FE	No	No	No	No	Yes
Adj. R^2	0.050	0.074	0.080	0.085	0.113
N	1,044	1,044	1,044	757	650

Panel B: CAR(-3,3)

Dep. var.:	CAR(-3,3) of public-target acquirers				
	(1)	(2)	(3)	(4)	(5)
GapSignal	-0.041***	-0.043***	-0.044***	-0.058***	-0.061***
	(-3.36)	(-3.15)	(-3.16)	(-2.63)	(-2.72)
Alignment		-0.010	-0.007	-0.006	-0.005
		(-0.99)	(-0.43)	(-0.27)	(-0.21)
% in cash		0.027***	0.018**	0.035***	0.034***
		(3.42)	(2.18)	(2.96)	(2.84)
Log asset (A)			0.006***	0.011***	0.012***
			(2.61)	(3.27)	(3.64)
Log asset (T)			-0.005*	-0.011***	-0.010**
			(-1.76)	(-2.71)	(-2.45)
Deal controls	No	Yes	Yes	Yes	Yes
Firm controls	No	No	Yes	Yes	Yes
Year, AInd, TInd FE	Yes	Yes	Yes	No	No
AInd × Year, Tind × Year FE	No	No	No	Yes	No
AInd × Tind × Year FE	No	No	No	No	Yes
Adj. R^2	0.044	0.052	0.055	0.053	0.083
N	1,044	1,044	1,044	757	650

Table 3: Acquirer returns and revealed gaps with private targets. This table reports the regression results of Equation (33) based on a sample of private-target acquisitions. The dependent variables are the acquirer's CARs over two event windows: CAR(-1,1) in Panel A and CAR(-3,3) in Panel B. The main independent variable of interest is *GapSignal*, which captures the acquirer's technological gap revealed by the acquisition. Only a subset of control variables is shown for brevity; a complete list is provided in Section 3.2.3. *AInd* and *TInd* denote the 2-digit SIC industries of the acquirer and the target, respectively. All other variables are defined in Table A2. T-statistics are reported in brackets. Standard errors are robust to heteroskedasticity. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: CAR(-1,1)

Dep. var.:	CAR(-1,1) of private-target acquirers				
	(1)	(2)	(3)	(4)	(5)
GapSignal	-0.012	0.001	0.010	0.035	0.028
	(-0.73)	(0.07)	(0.60)	(1.40)	(1.07)
Alignment		-0.031**	-0.045**	-0.031	-0.037
		(-2.58)	(-2.52)	(-1.19)	(-1.39)
% in cash		-0.016	-0.008	-0.016	-0.014
		(-1.64)	(-0.84)	(-1.24)	(-1.07)
Log asset (A)			-0.013***	-0.009**	-0.011**
			(-4.59)	(-2.48)	(-2.58)
Log asset (T)			0.003	-0.002	0.000
			(1.03)	(-0.40)	(0.10)
Deal controls	No	Yes	Yes	Yes	Yes
Firm controls	No	No	Yes	Yes	Yes
Year, AInd, TInd FE	Yes	Yes	Yes	No	No
AInd × Year, Tind × Year FE	No	No	No	Yes	No
AInd × Tind × Year FE	No	No	No	No	Yes
Adj. R^2	0.114	0.124	0.149	0.048	0.021
N	962	962	962	711	559

Panel B: CAR(-3,3)

Dep. var.:	CAR(-3,3) of private-target acquirers				
	(1)	(2)	(3)	(4)	(5)
GapSignal	-0.012	0.005	0.008	0.002	-0.005
	(-0.71)	(0.29)	(0.43)	(0.05)	(-0.16)
Alignment		-0.048***	-0.062***	-0.044	-0.033
		(-3.61)	(-3.11)	(-1.46)	(-1.05)
% in cash		-0.015	-0.009	-0.030*	-0.025
		(-1.26)	(-0.79)	(-1.69)	(-1.53)
Log asset (A)			0.004	-0.002	0.000
			(1.30)	(-0.39)	(0.04)
Log asset (T)			0.004	0.001	0.000
			(1.41)	(0.14)	(-0.01)
Deal controls	No	Yes	Yes	Yes	Yes
Firm controls	No	No	Yes	Yes	Yes
Year, AInd, TInd FE	Yes	Yes	Yes	No	No
AInd × Year, Tind × Year FE	No	No	No	Yes	No
AInd × Tind × Year FE	No	No	No	No	Yes
Adj. R^2	0.051	0.064	0.071	-0.041	0.017
N	962	962	962	711	559

Table 4: Exceptionally transparent private targets. This table replicates Table 3, while interacting *GapSignal*—the proxy for the acquirer's revealed technological gap—with an indicators for exceptionally transparent targets. *Transparent target* equals 1 if the target has issued corporate bonds or other securities prior to the acquisition announcement, and 0 otherwise. The dependent variables are the acquirer's CARs over two event windows: CAR(-1,1) in Panel A and CAR(-3,3) in Panel B. Control variables are omitted for brevity; a complete list is provided in Section 3.2.3. *AInd* and *TInd* denote the 2-digit SIC industries of the acquirer and the target, respectively. All other variables are defined in Table A2. T-statistics are reported in brackets. Standard errors are robust to heteroskedasticity. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: CAR(-1,1)

Dep. var.:	CAR(-1,1) of private-target acquirers				
	(1)	(2)	(3)	(4)	(5)
GapSignal × Transparent target	-0.172**	-0.184**	-0.193***	-0.160	-0.269**
	(-2.18)	(-2.28)	(-2.63)	(-1.40)	(-2.53)
GapSignal	-0.003	0.012	0.021	0.040	0.038
	(-0.18)	(0.68)	(1.24)	(1.61)	(1.43)
Transparent target	0.084	0.088	0.090*	0.046	0.135*
	(1.59)	(1.60)	(1.84)	(0.54)	(1.77)
Deal controls	No	Yes	Yes	Yes	Yes
Firm controls	No	No	Yes	Yes	Yes
Year, AInd, TInd FE	Yes	Yes	Yes	No	No
AInd × Year, Tind × Year FE	No	No	No	Yes	No
AInd × Tind × Year FE	No	No	No	No	Yes
Adj. R^2	0.119	0.131	0.157	0.055	0.033
N	962	962	962	711	559

Panel B: CAR(-3,3)

Dep. var.:	CAR(-3,3) of private-target acquirers				
	(1)	(2)	(3)	(4)	(5)
GapSignal × Transparent target	-0.196**	-0.201***	-0.206***	-0.204	-0.314***
	(-2.55)	(-2.59)	(-2.70)	(-1.64)	(-2.60)
GapSignal	-0.001	0.017	0.020	0.008	0.006
	(-0.05)	(0.94)	(1.00)	(0.25)	(0.16)
Transparent target	0.085*	0.084*	0.086*	0.051	0.126
	(1.75)	(1.67)	(1.77)	(0.60)	(1.55)
Deal controls	No	Yes	Yes	Yes	Yes
Firm controls	No	No	Yes	Yes	Yes
Year, AInd, TInd FE	Yes	Yes	Yes	No	No
AInd × Year, Tind × Year FE	No	No	No	Yes	No
AInd × Tind × Year FE	No	No	No	No	Yes
Adj. R^2	0.058	0.071	0.079	-0.030	0.034
N	962	962	962	711	559

Table 5: Predicting gap bidders. This table presents estimation results of Equation (29). The dependent variable *GapSignal* measures the acquirer's technological gap revealed by the target's technological profile. The dependent variables are acquisition antecedents discussed in Section 4.4.1. *AInd* and *TInd* denote the 2-digit SIC industries of the acquirer and the target, respectively. All other variables are defined in Table A2. T-statistics are reported in brackets. Standard errors are robust to heteroskedasticity. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Sample:	Acquirers of public targets							
Dep. var.:	*GapSignal*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R&D/asset	0.249***							0.241***
	(5.48)							(4.81)
ΔR&D/asset	-0.147***							-0.162***
	(-3.46)							(-3.58)
Patent index	0.000							0.000
	(0.49)							(-0.64)
ΔPatent index	0.0001*							0.000
	(1.67)							(1.42)
Log asset		0.013***						0.019***
		(2.68)						(3.52)
Log patent stock		0.006						0.003
		(1.63)						(0.89)
Age		-0.002***						-0.002**
		(-2.73)						(-2.21)
Log Tobin's Q			0.050***					0.038**
			(3.60)					(2.39)
Productivity			0.031**					0.031**
			(2.26)					(2.05)
Cash flow/asset				-0.011				-0.053**
				(-0.55)				(-2.50)
Cash/asset				0.035				-0.001
				(0.66)				(-0.02)
Market leverage				-0.184**				-0.116
				(-1.97)				(-1.13)
Capex/asset					-0.207			-0.269
					(-1.01)			(-1.30)
Sales growth					-0.020			-0.064***
					(-0.86)			(-2.82)
Competition						-0.843***		-0.835***
						(-2.66)		(-2.67)
Tech competition						0.146		0.173
						(1.32)		(1.56)
Female executive							0.033	0.022
							(1.55)	(1.03)
Female CEO							0.010	0.014
							(0.20)	(0.28)
Year, AInd, TInd FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.370	0.367	0.369	0.361	0.358	0.361	0.359	0.390
N	1,044	1,044	1,044	1,044	1,044	1,044	1,044	1,044

Table 6: Prediction or suprise? This table replicates Columns (3)–(5) in Table 2, Panel A and Panel B, while decomposing *GapSignal*—the proxy for the acquirer's revealed technological gap—into a fitted value that is predicted by acquisition antecedents discussed in Section 4.4.1, and a residual that capture information orthogonal to observable acquirer characteristics. The dependent variables are the acquirer's CARs over two event windows: CAR(-1,1) and CAR(-3,3). Control variables are omitted for brevity; a complete list is provided in Section 3.2.3. *AInd* and *TInd* denote the 2-digit SIC industries of the acquirer and the target, respectively. All other variables are defined in Table A2. T-statistics are reported in brackets. Standard errors are robust to heteroskedasticity. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Sample:	Acquirers of public targets					
Dep. var.:	CAR(-1,1)			CAR(-3,3)		
	(1)	(2)	(3)	(4)	(5)	(6)
GapSignal (fitted)	-0.017	-0.082	-0.071	-0.071	-0.111	-0.102
	(-0.21)	(-0.76)	(-0.64)	(-1.03)	(-1.17)	(-1.09)
GapSignal (residual)	-0.030**	-0.058***	-0.057***	-0.043***	-0.055**	-0.059***
	(-2.54)	(-3.12)	(-2.97)	(-3.04)	(-2.51)	(-2.65)
Firm, deal controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, AInd, TInd FE	Yes	No	No	Yes	No	No
AInd × Year, Tind × Year FE	No	Yes	No	No	Yes	No
AInd × Tind × Year FE	No	No	Yes	No	No	Yes
Adj. R^2	0.079	0.084	0.111	0.055	0.052	0.081
N	1,044	757	650	1,044	757	650

Table 7: Overpayment? This table replicates Columns (3)–(5) in Table 2, Panel A and Panel B for public targets. The dependent variable *GapSignal* proxies for the acquirer's revealed technological gap. The dependent variables are the target's CARs over two event windows: CAR(-1,1) and CAR(-3,3). Only a subset of control variables are reported for brevity; a complete list is provided in Section 3.2.3. *AInd* and *TInd* denote the 2-digit SIC industries of the acquirer and the target, respectively. All other variables are defined in Table A2. T-statistics are reported in brackets. Standard errors are robust to heteroskedasticity. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Sample:	Public targets					
Dep. var.:	CAR(-1, 1)			CAR(-3, 3)		
	(1)	(2)	(3)	(4)	(5)	(6)
GapSignal	-0.017	-0.082	-0.071	-0.071	-0.111	-0.102
	(-0.21)	(-0.76)	(-0.64)	(-1.03)	(-1.17)	(-1.09)
Alignment	-0.030**	-0.058***	-0.057***	-0.043***	-0.055**	-0.059***
	(-2.54)	(-3.12)	(-2.97)	(-3.04)	(-2.51)	(-2.65)
% in cash	-0.012	-0.008	-0.003	-0.006	-0.003	-0.003
	(-1.00)	(-0.44)	(-0.17)	(-0.37)	(-0.15)	(-0.12)
Tender offer	0.018**	0.029***	0.026***	0.018**	0.035***	0.034***
	(2.53)	(2.87)	(2.63)	(2.18)	(2.97)	(2.85)
Log asset (A)	0.015*	0.026**	0.032**	0.014	0.019	0.023
	(1.67)	(2.03)	(2.48)	(1.33)	(1.30)	(1.53)
Log asset (T)	0.005**	0.009***	0.009***	0.006***	0.011***	0.012***
	(2.25)	(2.86)	(2.80)	(2.65)	(3.32)	(3.66)
Firm, deal controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, AInd, TInd FE	Yes	No	No	Yes	No	No
AInd × Year, Tind × Year FE	No	Yes	No	No	Yes	No
AInd × Tind × Year FE	No	No	Yes	No	No	Yes
Adj. R^2	0.079	0.084	0.111	0.055	0.052	0.081
N	1,044	757	650	1,044	757	650

Table 8: Anticipation? This table replicates Columns (3) and (5) in Table 2, Panel A and Panel B for acquirers of public targets. The dependent variable *GapSignal* proxies for the acquirer's revealed technological gap. The dependent variables are the target's CARs over two event windows: CAR(-1,1) and CAR(-3,3), as well as their absolute values. Control variables are omitted for brevity; a complete list is provided in Section 3.2.3. $AInd$ and $TInd$ denote the 2-digit SIC industries of the acquirer and the target, respectively. All other variables are defined in Table A2. T-statistics are reported in brackets. Standard errors are robust to heteroskedasticity. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: CAR(-1,1)

Sample:	Acquirers of public targets					
Dep. var.:	|CAR(-1,1)|		CAR(-1,1)			
Subsample:	All		CAR(-1,1) $<$ 0		CAR(-1,1) $\geq$ 0	
	(1)	(2)	(3)	(4)	(5)	(6)
GapSignal	0.024***	0.039***	0.011	0.006	-0.038***	-0.066***
	(2.97)	(3.12)	(0.96)	(0.34)	(-3.25)	(-3.11)
Firm, deal controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, AInd, TInd FE	Yes	No	Yes	No	Yes	No
AInd × Tind × Year FE	No	Yes	No	Yes	No	Yes
Adj. R^2	0.189	0.249	0.265	0.250	0.202	0.195
N	1,044	650	460	265	555	303

Panel B: CAR(-3,3)

Sample:	Acquirers of public targets					
Dep. var.:	|CAR(-3,3)|		CAR(-3,3)			
Subsample:	All		CAR(-3,3) $<$ 0		CAR(-3,3) $\geq$ 0	
	(1)	(2)	(3)	(4)	(5)	(6)
GapSignal	0.025**	0.051***	0.005	0.011	-0.064***	-0.078***
	(2.53)	(3.37)	(0.34)	(0.35)	(-3.85)	(-2.69)
Firm, deal controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, AInd, TInd FE	Yes	No	Yes	No	Yes	No
AInd × Tind × Year FE	No	Yes	No	Yes	No	Yes
Adj. R^2	0.167	0.183	0.050	0.005	0.094	0.068
N	1,044	650	460	265	555	303

Table 9: Redefining the gap measure. This table replicates Table 2, while redefining the dependent variable *GapSignal*—the proxy for the acquirer's revealed technological gap—based on CPC subclasses. The dependent variables are the acquirer's CARs over two event windows: CAR(-1,1) in Panel A and CAR(-3,3) in Panel B. Control variables are omitted for brevity; a complete list is provided in Section 3.2.3. *AInd* and *TInd* denote the 2-digit SIC industries of the acquirer and the target, respectively. All other variables are defined in Table A2. T-statistics are reported in brackets. Standard errors are robust to heteroskedasticity. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: CAR(-1,1)

Dep. var.:	CAR(-1,1) of public-target acquirers				
	(1)	(2)	(3)	(4)	(5)
GapSignal (subclass)	-0.016*	-0.021**	-0.022*	-0.049***	-0.048***
	(-1.71)	(-1.98)	(-1.92)	(-2.86)	(-2.79)
Deal controls	No	Yes	Yes	Yes	Yes
Firm controls	No	No	Yes	Yes	Yes
Year, AInd, TInd FE	Yes	Yes	Yes	No	No
AInd × Year, Tind × Year FE	No	No	No	Yes	No
AInd × Tind × Year FE	No	No	No	No	Yes
Adj. R^2	0.046	0.071	0.078	0.081	0.111
N	1,044	1,044	1,044	757	650

Panel B: CAR(-3,3)

Dep. var.:	CAR(-3,3) of public-target acquirers				
	(1)	(2)	(3)	(4)	(5)
GapSignal (subclass)	-0.031***	-0.035***	-0.037***	-0.060***	-0.068***
	(-2.80)	(-2.75)	(-2.76)	(-2.99)	(-3.40)
Deal controls	No	Yes	Yes	Yes	Yes
Firm controls	No	No	Yes	Yes	Yes
Year, AInd, TInd FE	Yes	Yes	Yes	No	No
AInd × Year, Tind × Year FE	No	No	No	Yes	No
AInd × Tind × Year FE	No	No	No	No	Yes
Adj. R^2	0.040	0.050	0.053	0.057	0.091
N	1,044	1,044	1,044	757	650

Table 10: Target revaluation. This table replicates Table 7, while introducing additional regressors. *GapSignal* and *GapSignal* (T) measure the revealed technological gap of the acquirer and the target, respectively. *Alignment* and *Alignment* (T) measure the observable technological standing relative to the technological frontier of the acquirer and the target, respectively. The Dependent variables are the target's CARs over two event windows: CAR(-1,1) and CAR(-3,3). Other control variables are omitted for brevity; a complete list is provided in Section 3.2.3. $AInd$ and $TInd$ denote the 2-digit SIC industries of the acquirer and the target, respectively. All other variables are defined in Table A2. T-statistics are reported in brackets. Standard errors are robust to heteroskedasticity. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Sample:	Public targets					
Dep. var.:	CAR(-1,1)			CAR(-3,3)		
	(1)	(2)	(3)	(4)	(5)	(6)
GapSignal	-0.006	-0.048	0.282	-0.018	-0.100	0.110
	(-0.09)	(-0.27)	(0.79)	(-0.27)	(-0.56)	(0.30)
GapSignal (T)	-0.156**	-0.229	-0.150	-0.141*	-0.245	-0.327
	(-2.08)	(-1.33)	(-0.65)	(-1.73)	(-1.37)	(-1.33)
Alignment	0.080	0.179	0.092	0.015	0.176	0.252
	(1.14)	(1.03)	(0.41)	(0.18)	(0.97)	(1.09)
Alignment (T)	0.068	0.139	-0.195	0.064	0.160	-0.061
	(1.16)	(0.78)	(-0.55)	(1.00)	(0.94)	(-0.17)
Firm, deal controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, AInd, TInd FE	Yes	No	No	Yes	No	No
AInd × Year, Tind × Year FE	No	Yes	No	No	Yes	No
AInd × Tind × Year FE	No	No	Yes	No	No	Yes
Adj. R^2	0.079	0.084	0.111	0.055	0.052	0.081
N	1,044	757	650	1,044	757	650