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The Journal of Industrial Economics

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ORIGINAL ARTICLE OPEN ACCESS

Make or Buy Decisions and Data Sharing

Antoine Dubus[1] | Patrick Legros[2]

[1]Department of Management, Technology, and Economics, ETH Zürich, Zürich, Switzerland | [2]ECARES and CEPR, Université Libre de Bruxelles, Brussels, Belgium

Correspondence: Antoine Dubus (antoine1dubus@gmail.com)

Accepted: 30 April 2026

Keywords: antitrust | artificial intelligence | incomplete information | mergers and acquisitions | synergies

ABSTRACT

Firms can share data to discover potential synergies between their data sets and algorithms, eventually leading to more efficient mergers and acquisitions (M&A) decisions. However, data sharing also modifies the competitive balance when firms do not merge, and a company may be reluctant to share data with potential rivals. Under general conditions, we show that firms benefit from (partially) sharing data. By doing so, they can merge conditionally based on high synergies. Compared to a laissez-faire situation, the presence of a regulator allowing or refusing the M&A may increase or decrease data sharing, with a concomitant increase or decrease in consumer surplus. Hence, regulation can *reduce the surplus* of consumers it is willing to protect. We revisit the Google/Fitbit acquisition through the lens of this interplay between strategic data sharing and antitrust policy.

JEL Classification: G34, K21, L1, L21, L24, L5, L86

Pre-merger information gaps, whether from overoptimistic synergy assessments or uncertainty about data complementarities, can cause costly M&A failures. Reducing these gaps before an acquisition is valuable, but information sharing plays a dual role: it is both a screening device for merger efficiency and a competitive instrument that remains active if the merger does not occur. We show that this tension shapes firms' incentives to share data, the conditions under which mergers take place, and the welfare effects of merger control, a link that the literature has not formalized.

We develop the analysis through the lens of digital markets, where these forces are particularly salient. Data sharing is increasingly common among firms, including direct competitors [1, 2]. Digital firms seek vast amounts of data to train AI systems,[1] generate data-driven network effects [3], and benefit from identifying externalities across consumer groups [4]. Data acquisition has become a major driver of many M&As [5, 6].[2] Yet digital M&As are risky and many fail to deliver expected benefits [7].[3] Synergies between firms' data and algorithms are unknown before the merger, firms may only have a probabilistic estimate, and their actual value can be assessed only after integrating the target's data and retraining algorithms.[4] As Experian notes, data quality and data/algorithm synergies are increasingly central to digital M&As but also generate major uncertainty about merger outcomes.[5] Accurately anticipating these synergies is thus crucial both for merging firms and for regulators seeking to protect consumers.[6]

We study these mechanisms through Google's 2.1 billion USD acquisition of Fitbit, completed in 2021, which provides unusually detailed evidence of each mechanism the model identifies [8]. Before the acquisition, Fitbit progressively migrated a subset of its application data to Google Cloud, enabling Google to learn the complementarity between the firms' data assets while limiting competitive exposure. As Google Cloud's own press release noted, the partnership enabled Google to "explor[e] how Google Cloud's machine learning APIs can help them uncover deeper insights":[7] precisely the synergy-learning mechanism our model describes. The model also applies to other contexts where

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pre-merger data sharing facilitates learning about complementarities, including Facebook/WhatsApp, where detailed user profiles were at stake, and Apple/Shazam, where the European Commission examined how access to the target's data could alter market power.[8] In the model, Google considers acquiring Fitbit; before the acquisition, Fitbit can share data with Google, which uses it to learn the value of potential synergies at an exploration cost. If synergies are high the merger is efficient; if they are low, continued competition is preferable.

Pre-merger data sharing strictly dominates merging under incomplete information: by conditioning the acquisition on realized synergies, firms avoid inefficient mergers and capture the resulting option value, even when data sharing intensifies competition. This option value is sufficiently large that, under general conditions, firms benefit from partial data sharing even though it strengthens a potential rival. A direct implication is that pre-merger data sharing to assess synergies is likely already embedded in data-driven M&A practice, the Google/Fitbit data migration, widely interpreted at the time as a precursor to acquisition,[9] is consistent with this prediction.

The growing importance of data in digital markets has led to calls for updated regulation to protect competition and consumers, especially in merger control [9, 10]. Our analysis identifies a previously overlooked cost of merger control: by constraining firms' sharing strategies, a regulator can deter the very data sharing that would have intensified competition in the event the merger is blocked. The result is that strict merger control can reduce consumer surplus relative to laissez-faire, a novel argument that challenges the traditional case for stringent review. This suggests that merger control and data-sharing mandates are complements rather than substitutes: combining them can preserve firms' incentives to learn about synergies while protecting consumers, a connection that recent regulation, including Article 32 of the European Data Act,[10] has begun to make, but that has not been theoretically grounded.

The remainder of this article is structured as follows. Section 1 surveys the literature on data sharing and data-driven mergers and acquisitions (M&As). Section 2 introduces the model, and Section 3 characterizes the equilibrium. Section 4 examines how regulatory interventions influence data sharing and surplus. Section 5 derives the corresponding policy implications, and Section 6 provides an in-depth analysis of the Google/Fitbit acquisition. Section 7 concludes.

1 | Related Literature

The paper sits at the intersection of three literatures, data sharing among rivals, data-driven mergers, and digital market regulation, and its contribution to each follows from the same underlying mechanism: because data sharing resolves uncertainty about merger synergies, it generates an option value that neither the data sharing literature nor the M&A literature, taken separately, can capture.

1.1 | Data Sharing Among Rivals

A large literature studies strategic data sharing, emphasizing its effects on competition and industry profits. Sharing can intensify competition and reduce profits [11–13], or soften competition through improved targeting or coordination [1, 14, 15]. Reference [16] identify a distinct channel: data sharing is profitable when it links separate markets and enables co-opetition, so that competitive losses in one market are offset by gains elsewhere. Our contribution is different in kind. We show that data sharing can be profitable even when it unambiguously reduces competitive profits, a case that existing models treat as a deterrent to sharing. The reason is that the option to merge conditionally on realized synergies creates a value that dominates the competitive loss. This option-value logic operates through the merger decision and is simply unavailable in models that abstract from M&A incentives.

1.2 | Data-Driven Mergers and Acquisitions

The growing literature on data-driven M&A typically takes the merger decision as given, mergers are assumed to be ex-ante profitable, and studies their effects on prices, quality, or consumer surplus [5, 8, 17]. By fixing the merger decision, these models are structurally not developed to study how pre-merger information acquisition shapes whether a merger occurs at all. We endogenize this decision: firms merge only when data sharing reveals high synergies, and the threat of competition if synergies are low disciplines both the sharing decision and the acquisition price. This changes positive predictions, data sharing increases efficient M&A rates and reduces merger failures, and normative conclusions, since a regulator focused on post-merger market structure may inadvertently destroy the pre-merger competition it aims to protect.

1.3 | Regulation of Digital Markets

A policy literature argues that data-sharing mandates promote competition and contestability in digital markets [9, 10]. This literature evaluates sharing rules primarily through their direct effects on competitive intensity. We show that sharing rules have a second indirect effect: they alter firms' incentives to learn about synergies and, therefore, influence both the frequency and efficiency of mergers. Post-merger remedies such as data silos, analyzed here for the first time in the context of pre-merger sharing incentives, feed back into firms' strategies before a deal is struck. The implication is that merger control and data regulation are complements, not substitutes: a regulator focused solely on post-merger outcomes risks deterring the pre-merger data sharing that would have strengthened the competition it seeks to preserve.

2 | Model

The model captures a market in which an incumbent supplier of data-intensive products faces a potential acquirer who can learn about synergies before deciding whether to merge. Fitbit (indexed by F) provides wearable devices. Google (indexed by G) is initially not active in this product market but earns profits in several technologically and commercially related markets and provides cloud services to firms such as Fitbit.[11]

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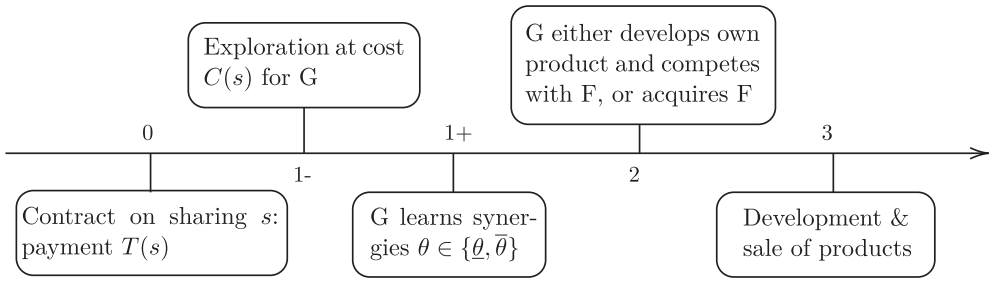


FIGURE 1 | Sequence of events.

At the initial stage of the interaction, firms $i \in \{F, G\}$ earn baseline profits denoted by π_i^0.[12] We adopt a reduced-form specification of the profit functions. This nonparametric approach isolates the economic mechanisms associated with data sharing more transparently than a fully specified model would. Appendix A.1 derives explicit parametric representations within linear demand oligopoly models, where demand intercepts depend on the extent of data sharing.

The sequence of actions is summarized in Figure 1. In the first stage, Fitbit chooses whether and at what intensity to share a subset of its data with Google. The contractual arrangement specifies a transfer $T(s)$ as a function of the chosen level of data-sharing s.

Google's decision to incur an exploration cost and the subsequent learning of synergies are decomposed into two sub-stages, 1− and 1+, for clarity. At stage 2, an information revelation problem arises: Google privately observes the realized synergies, while Fitbit does not. We show that this information can be credibly transmitted through Google's merger decision: Google proposes an acquisition only when synergies are high, allowing Fitbit to infer the realization of θ from whether an offer is made.

2.1 | Sharing and Contracting

Firms have a stock of data generated in the course of their economic activities. Fitbit can share a proportion $s \in [0, 1]$ of its data with Google, either unilaterally or in exchange for a lump-sum transfer $T(s)$.[13]

2.2 | Synergies and Exploration

The use of Fitbit's data on Google's platform generates synergies of value $\theta \in \{\underline{\theta}, \overline{\theta}\}$, with $\overline{\theta} > \underline{\theta}$, affecting both firms' profits and consumer surplus. These synergies may be operational, arising from efficiency gains when Fitbit's systems run on Google Cloud, or stem from positive cross-market data spillovers once Fitbit is integrated into Google's broader platform ecosystem. The true realization of θ is initially unknown; each firm shares a common prior under which $\theta = \underline{\theta}$ with probability α and $\theta = \overline{\theta}$ with probability $1 - \alpha$.[14]

By exploring Fitbit's shared data, Google can learn the realized value of θ and, conditional on this information, develop a product that leverages the data. Inferring the total synergistic value from a subset s entails an exploration cost $C(\cdot)$. The literature on statistics and machine learning shows that inferring information from missing data is costly and that performance improves with data volume (see, e.g., [18]). We therefore assume that $C(\cdot)$ decreases with s. Assuming $C(1) = 0$ and the Inada conditions below is for analytical convenience and can be relaxed without changing the qualitative results.

$$\text{Exploration cost: } C(.),\ C''(.) \geq 0,\ C(0) = +\infty,\ C'(0) = -\infty,\ \&\ C'(1) = C(1) = 0. \tag{H1}$$

These specifications are consistent with recent empirical evidence on economies of scope and scale in data aggregation [19, 20]. Other costs, such as storing and analyzing data or developing new algorithms, are embedded in the profit functions for simplicity.

2.3 | Google's Acquisition Strategy

Google can acquire Fitbit either under incomplete information (no prior data sharing) or with full information after exploring Fitbit's shared data. Firms thus face three options at the start of the game: compete without sharing; Google acquires Fitbit without prior data sharing; or data sharing followed by exploration and an acquisition decision conditional on the realized synergy state. Acquisitions are assumed final; divestment is prohibitively costly.[15]

2.4 | Competition Following Data Sharing

After exploring the shared data and learning the synergy value, Google can enter the market with a stronger competitive position: the shared data enables more accurate algorithmic predictions, personalized recommendations, and better integration with its service ecosystem, increasing Google's appeal to consumers.

2.5 | Arrow Effect

This improvement reduces Fitbit's market share and lowers its profit [11, 12]; the adverse effect grows with s since more data enables Google to train more efficient models. The profits under competition are denoted $\pi_i^C(s, \theta)$, continuous in s for any given θ, and satisfy:

$$\text{Arrow effect: } \frac{\partial \pi_G^C(s,\theta)}{\partial s} \geq 0 \geq \frac{\partial \pi_F^C(s,\theta)}{\partial s}. \tag{H2}$$

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Denoting $\pi^C(s,\theta) := \pi_F^C(s,\theta) + \pi_G^C(s,\theta)$ the joint competitive profit, H2 leaves open whether sharing raises or lowers joint profits. We focus on the case where it reduces them at low synergies: H2 then requires that Fitbit's competitive loss dominates Google's gain, so that sharing erodes the total industry surplus when synergies are low.

$$\text{Aggregate profits loss with low synergies: } \frac{\partial \pi^C(s,\underline{\theta})}{\partial s} \leq 0. \quad \text{(H3)}$$

The machine-learning literature provides evidence that total profits can fall with data sharing [21] illustrate this with traffic data among ride-hailing firms, and [22] study payment data in banking. Data sharing can also raise joint profits of firms [1], for instance by enabling coordination; in that case, H3 would not bind and the firms would freely share data to boost competitive profits. The tradeoff between competitive loss and efficiency gain is meaningful precisely when H2 and H3 both hold, making firms initially reluctant to share.

In the limit case $s = 0$, firms earn baseline competitive profits independent of θ:

$$\forall i, \theta, \ \pi_i^C(0,\theta) = \pi_i^0. \quad (1)$$

2.6 | Data–Synergy Complementarities

When synergies are high, Google can more effectively exploit the shared data to enhance product quality and analytics. The marginal value of additional data therefore increases with the level of synergies, and conversely:

$$\text{Data-synergies complementarity: } \frac{\partial^2 \pi_G^C(s,\theta)}{\partial s \partial \theta} \geq 0. \quad \text{(H4)}$$

This complementarity is supported by empirical evidence of super-additive returns to data when models are used for multiple tasks [23]. H4 is also necessary for the separating equilibrium we characterize below: it ensures that the gain to Google from acquiring Fitbit is sufficiently larger under high synergies than under low synergies to deter mimicry.

2.7 | Acquisition Under Imperfect Information (Benchmark)

Before introducing the data-sharing case, it is useful to characterize the benchmark in which firms merge without prior information acquisition. When firms merge under incomplete information, the merged firm earns $\pi^A(\overline{\theta})$ when synergies are high (prob. $1-\alpha$) and $\pi^A(\underline{\theta})$ when synergies are low (prob. α). After the acquisition, Google has access to all Fitbit data at no inference cost ($C(1) = 0$). The expected payoff is

$$\mathbb{E}[\pi^A;\alpha] := (1-\alpha)\pi^A(\overline{\theta}) + \alpha\ \pi^A(\underline{\theta}),$$

and the acquisition is beneficial only if

$$\mathbb{E}[\pi^A;\alpha] - \pi^0 \geq 0. \quad (2)$$

Merger gains are shared via Nash bargaining [24–26]. With Fitbit's bargaining weight $\mu \in [0,1]$ and Google's $1-\mu$, the Nash payoffs are:

$$u_F(\alpha) := \pi_F^0 + \mu\big(\mathbb{E}[\pi^A;\alpha] - \pi^0\big),$$
$$u_G(\alpha) := \pi_G^0 + (1-\mu)\big(\mathbb{E}[\pi^A;\alpha] - \pi^0\big).$$

Google offers a price $p^A = u_F(\alpha)$ to Fitbit and receives $u_G(\alpha)$. Without data sharing, Google acquires Fitbit only when condition (2) holds, that is, when the merger is ex-ante efficient.

2.8 | Acquisition With Data Sharing

When firms merge after data sharing, the merged firm earns profits $\pi^A(\theta)$ that depend on the synergy realized. For data sharing to create an option value, we require the merger to be jointly profitable if and only if synergies are high:

$$\text{Option value: } \forall s, \pi^A(\overline{\theta}) > \pi^C(s,\overline{\theta}),$$
$$\&\ \ \pi^A(\underline{\theta}) < \pi^C(s,\underline{\theta}). \quad \text{(H5)}$$

Combined with (1), H5 implies $\pi^A(\overline{\theta}) > \pi^A(\underline{\theta})$. Outside H5, the merger decision is trivial: Google either always or never wants to acquire Fitbit regardless of the synergy realization, making data sharing uninformative. When synergies are low, profit losses reflect merger costs, cultural shocks, and incompatibilities between the firms' information systems.[16] Data sharing enables firms to avoid such mergers. Obtaining this option is costly: Google pays the exploration cost $C(s)$ and, when synergies are low, the joint competitive profit falls under H3.

Acquisition negotiations occur under asymmetric information: after exploration, Google knows privately θ while Fitbit does not. Three candidate equilibria arise: (i) separating, where Google offers to acquire Fitbit only when synergies are high; (ii) pooling on merger; and (iii) pooling on competition.[17] Profit division again follows Nash bargaining with the same weights μ and $1-\mu$.[18] In a separating equilibrium the acquisition decision is contingent on θ and must satisfy an incentive-compatibility condition.

3 | Equilibrium Analysis

We characterize the sequential equilibria of this game by backward induction. We first solve stage 2 conditional on a given level of sharing s, then derive the optimal level of sharing at stage 0.

3.1 | Profits With Data Sharing

Suppose that Fitbit shares s with Google, who explores the data at cost $C(s)$ and privately learns θ. Three candidates for equilibrium arise at stage 2: (i) separating; (ii) pool-to-acquire; (iii) pool-to-compete.

Pool-to-acquire is dominated by merging under incomplete information: the expected surplus from the acquisition is the same, but Google incurs the exploration cost $C(s)$. We therefore focus

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on separation and pool-to-compete. H4 is necessary for a separating equilibrium to exist. If a separating equilibrium exists, pool-to-compete is unstable under type-dominance refinements because there is a profitable deviation by $\overline{\theta}$ that is not profitable for $\underline{\theta}$. If separation is not possible, pool-to-compete can be made stable.

By standard arguments, the necessary condition for separation is $\pi^A(\overline{\theta}) - \pi^A(\underline{\theta}) \geq \pi_G^C(s,\overline{\theta}) - \pi_G^C(s,\underline{\theta})$. The left side is positive; the right side increases in s by H4.

Proposition 1. *There exists $\sigma \in (0,1]$ such that separation is the unique equilibrium if and only if $s \leq \sigma$, and pool-to-compete is the only equilibrium if $s > \sigma$. If there is separation, letting $p^*(s) = \pi_F^C(s,\overline{\theta}) + \mu(\pi^A(\overline{\theta}) - \pi^C(s,\overline{\theta}))$, the acquisition price in state $\overline{\theta}$ is*

$$p^A(s) = \begin{cases} p^*(s) & \text{if } p^*(s) \geq \pi^A(\underline{\theta}) - \pi_G^C(s,\underline{\theta}), \\ \pi^A(\overline{\theta}) - \pi_G^C(s,\overline{\theta}) & \text{if } p^*(s) \leq \pi^A(\underline{\theta}) - \pi_G^C(s,\underline{\theta}). \end{cases}$$

Proof. See the Appendix. □

When $\sigma \in (0,1)$, firms either share $s < \sigma$ and merge only when synergies are high, or share $s > \sigma$ and compete regardless of θ. The resulting profits are provided in Equation (9) of Section 4.3, where we analyze the equilibrium with a regulator. For the rest of the present section, we focus on $\sigma = 1$, so that after exploration there is acquisition only when the synergies are high.

3.1.1 | Stage 1: Sharing Decision

Anticipating an acquisition when synergies are high, the expected profit of Fitbit sharing s is $(1-\alpha)p^A(s) + \alpha\ \pi_F^C(s,\underline{\theta})$. By the Arrow effect, Fitbit may incur a competitive loss from sharing, in which case Google pays a transfer $T(s)$ to compensate and incentivize sharing. In practice, this transfer can take the form of a discount Google offers Fitbit for the use of its cloud services.

The transfer depends on Fitbit's outside option: competing at π_F^0, or merging under incomplete information at $u_F(\alpha) = \pi_F^0 + \mu\big(\mathbb{E}[\pi^A;\alpha] - \pi^0\big)$.

Lemma 1. *Google pays a transfer $T(s)$ to Fitbit to share s data, equal to*:

$$T(s) = \pi_F^0 + \max\{\mu\big(\mathbb{E}[\pi^A;\alpha] - \pi^0\big), 0\} - (1-\alpha)p^A(s) - \alpha\ \pi_F^C(s,\underline{\theta}).$$

Google acquires data only if it can recover both $C(s)$ and $T(s)$. Note that $T(s)$ can be negative when the acquisition price $p^A(s)$ is high, in which case Fitbit shares data for free and the game reduces to the acquisition stage. The optimal amount of data shared maximizes the ex-ante joint profit of Fitbit and Google:[19]

$$\Pi(s,\alpha) := (1-\alpha)\pi^A(\overline{\theta}) + \alpha\ \pi^C(s,\underline{\theta}) - C(s). \tag{3}$$

Ex-ante sharing thus creates an option for the merger decision: firms merge only when synergies are high, avoiding inefficient mergers when synergies are low.

3.1.2 | Optimal Sharing

An increase in s has two opposing effects on Google's expected profits. More data reduces the exploration cost $C(s)$ (under H1, using very little data is prohibitively costly), but also increases the transfer $T(s)$ because the competitive loss to Fitbit increases with s under H3. The equilibrium amount of data shared $s^*(\alpha)$ balances these effects and satisfies

$$\alpha \frac{\partial \pi^C(s^*(\alpha),\underline{\theta})}{\partial s} = C'(s^*(\alpha)). \tag{4}$$

We assume that a unique $s^*(\alpha)$ satisfies this condition, for example, when $\pi^C(s,\underline{\theta})$ is quasi-concave in $s \in (0,1)$.

3.2 | Equilibrium Data Sharing

Data will be shared before the merger if the maximum expected joint payoff under sharing, $\Pi^*(\alpha) := \Pi(s^*(\alpha),\alpha)$, exceeds both the expected payoff from merging under imperfect information and competitive profits:

$$\Pi^*(\alpha) \geq \max\{\mathbb{E}[\pi^A;\alpha], \pi^0\}.$$

If competition dominates a merger under incomplete information, sharing enables M&As conditional on high synergies. Otherwise, sharing allows firms to avoid mergers when synergies are low. We first show that data sharing always dominates merging under incomplete information, then characterize when it dominates pure competition.

3.2.1 | Sharing Data Dominates Merging Under Incomplete Information

Sharing gives Google the option to avoid mergers when synergies are low. The exploration cost and the competitive loss from sharing are offset by the gains from merger avoidance. Hence, without merger control, M&As with incomplete information do not occur when data sharing is possible, and mergers always occur after prior data sharing.

Proposition 2. *Data sharing is more profitable than merging with incomplete information.*

Proof. Rearranging the expression of the expected joint profit with data sharing:

$$\Pi(s,\alpha) = \mathbb{E}[\pi^A;\alpha] + \underbrace{\alpha(\pi^C(s,\underline{\theta}) - \pi^A(\underline{\theta}))}_{\substack{\text{Gains from merger} \\ \text{avoidance if } \underline{\theta},\ \text{H5}}} - \underbrace{C(s)}_{\substack{\text{Exploration} \\ \text{cost, H1}}}.$$

From (4), the equilibrium $s^*(\alpha)$ maximizes $\Pi(s,\alpha)$. Hence $\Pi^*(\alpha) \geq \Pi(1,\alpha) > \mathbb{E}[\pi^A;\alpha]$, which implies $\Pi^*(\alpha) \geq \mathbb{E}[\pi^A;\alpha]$. □

3.2.2 | Merging Vs. Competing

Although π^0 is independent of α, both $\mathbb{E}[\pi^A;\alpha]$ and $\Pi(s,\alpha)$ decrease with α (the probability of low synergies). When $\alpha = 0$,

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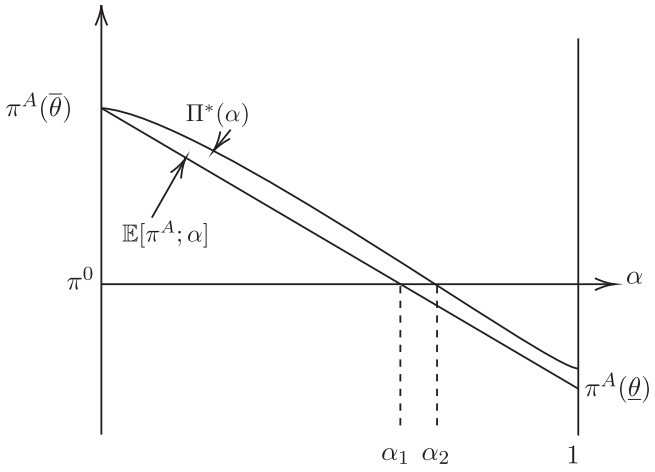


FIGURE 2 | Equilibrium gains from a merger without regulation.

they are both equal to $\pi^A(\overline{\theta})$,[20] Therefore, a necessary condition for a merger to occur is

$$\pi^A(\overline{\theta}) \geq \pi^0, \tag{5}$$

which is satisfied in our setting since $\pi^C(0,\theta) = \pi^0$ and $\pi^A(\overline{\theta}) > \pi^C(0,\theta)$ by H5. When $\alpha = 1$, H3 and H5 ensure that a merger is never profitable and firms always compete. By continuity, there exists α_1 such that firms are indifferent between merging under incomplete information and competing. Moreover, there exists α_2, with $0 < \alpha_1 < \alpha_2 < 1$, such that firms share data if and only if $\alpha \leq \alpha_2$. When $\alpha < \alpha_1$, sharing dominates merging under incomplete information: it allows firms to avoid mergers when synergies are low. When $\alpha_1 < \alpha < \alpha_2$, sharing dominates competition: it enables M&As when synergies are high. When $\alpha > \alpha_2$, firms compete without sharing. These results are illustrated in Figure 2.

Proposition 3. *There exist α_1 and α_2, with $0 < \alpha_1 < \alpha_2 < 1$ such that*:

i. *data sharing happens if, and only if, $\alpha \leq \alpha_2$,*
ii. *sharing prevents firms from merging when synergies are low if $\alpha \leq \alpha_1$ and allows mergers to occur when synergies are high if $\alpha \in (\alpha_1, \alpha_2]$.*

Firms can benefit from data sharing even with an excellent estimate (α close to one or zero). In this case, sharing almost all data is optimal because the likelihood that firms compete is low. Sharing and exploring offer the choice of not merging if synergies are low, with minimal exploration cost as $s^*(\alpha)$ is close to one. If the cost to learn synergies is always positive ($C(1) > 0$), merging with incomplete information is optimal for α close to zero only if Google has a high enough bargaining power (μ is small). In such cases, sharing is best for intermediate values of α. Data sharing expands the scope of profitable M&As, allowing mergers when $\alpha_1 < \alpha < \alpha_2$. Thus, data-sharing before merger should increase efficient M&A deals.

4 | Data Sharing in the Shadow of a Regulator

A regulator that approves only mergers increasing consumer surplus creates an unintended distortion: by constraining firms' sharing strategies, it deters the very data sharing that would have intensified competition in the event the merger is blocked. The result is that strict merger control can reduce consumer surplus relative to laissez-faire, a finding that challenges the standard case for stringent review.[21] This section characterizes equilibrium data sharing in the presence of a regulator, derives the welfare consequences, and identifies regulatory tools that can restore optimal outcomes.

4.1 | Assumptions on Consumer Surplus

Without data sharing, CS^0 denotes the baseline competitive consumer surplus. When a fraction s of the data is shared and firms compete in the state θ, the consumer surplus is $CS^C(s,\theta)$, assumed increasing in s:

$$\text{Consumer surplus: for all } (s,\theta), \frac{\partial CS^C(s,\theta)}{\partial s} \geq 0. \tag{H6}$$

When $s = 0$, baseline surplus is independent of the synergy state: $\forall\ \theta,\ CS^C(0,\theta) = CS^0$. The Post-merger consumer surplus $CS^A(\theta)$ depends on the realized synergies. The merger benefits consumers only when synergies are high,

$$CS^A(\overline{\theta}) > CS^0 > CS^A(\underline{\theta}), \tag{H7}$$

and full data sharing at high synergies makes competition strictly better for consumers than the merger,

$$CS^C(1,\overline{\theta}) > CS^A(\overline{\theta}). \tag{H8}$$

H7 and H8 together imply that there is a cap on how much data firms can share and still obtain merger approval: beyond a threshold, competition under high synergies dominates the merger for consumers, so the regulator blocks. This threshold is the central constraint driving the analysis. Both assumptions are consistent with the micro-foundations in Appendix A.1.1, where consumers benefit from higher product quality under high synergies and from more intense competition as s increases.

4.2 | Merger Control

Let $G(s,\theta) := CS^A(\theta) - CS^C(s,\theta)$ be the gain in consumer surplus from a merger when firms have shared s and the synergies are θ.

4.2.1 | Merger Control Without Data Sharing (Benchmark)

Without sharing, the regulator and firms anticipate an expected surplus gain of

$$\begin{aligned}\mathbb{E}[G(0,\theta)] &:= (1-\alpha)G(0,\overline{\theta}) + \alpha G(0,\underline{\theta}) \\ &= (1-\alpha)CS^A(\overline{\theta}) + \alpha CS^A(\underline{\theta}) - CS^0.\end{aligned} \tag{6}$$

Under H7, this expression is equal to $CS^A(\overline{\theta}) - CS^0 > 0$ when $\alpha = 0$ and $CS^A(\underline{\theta}) - CS^0 < 0$ when $\alpha = 1$, so it decreases monotonically with α. There exists a cutoff

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$$\alpha^R = \frac{CS^A(\bar{\theta}) - CS^0}{CS^A(\bar{\theta}) - CS^A(\underline{\theta})} \in (0,1) \tag{7}$$

such that the regulator accepts a merger with incomplete information only when $\alpha < \alpha^R$. From Proposition 3, merging under incomplete information dominates competition when $\alpha \le \alpha_1$, so the expected joint profit without sharing is

$$\Pi^R_{noshare}(\alpha) := \begin{cases} \mathbb{E}[\pi^A; \alpha] & \text{if } \alpha \le \min\{\alpha^R, \alpha_1\}, \\ \pi^0 & \text{if } \alpha > \min\{\alpha^R, \alpha_1\}. \end{cases} \tag{8}$$

4.2.1.1 | Merger Control With Data Sharing. When the regulator assesses a merger proposal, Fitbit has already shared s with Google. In a separating equilibrium, Google seeks approval only when synergies are high, so the regulator infers $\theta = \bar{\theta}$ from the merger request, and the change in consumer surplus does not depend on α. The details of the data-sharing transfer are recorded in both firms' financial statements and are accessible to the regulator during its review.

The regulator approves the merger if $G(s, \bar{\theta}) \ge 0$. H7 ensures approval when s is not too large; H8 ensures that excessively large s triggers blocking, since then competition dominates even at high synergies. Because $G(s, \bar{\theta})$ decreases with s, the regulator approves the merger if and only if

$$s \le \hat{s}^A,$$

where $\hat{s}^A \in [0,1]$ satisfies $CS^C(\hat{s}^A, \bar{\theta}) = CS^A(\bar{\theta})$. The constraint $s \le \hat{s}^A$ is the key regulatory friction: firms that would optimally share $s^*(\alpha) > \hat{s}^A$ must reduce their share to obtain approval or accept that the merger will be blocked.

Comparing $\hat{s}^A$ (the approval threshold for data sharing) with α^R (the cutoff for no sharing) reveals the regulator's asymmetric treatment of the two regimes: a merger under incomplete information is assessed on its expected surplus, whereas a merger after data sharing is assessed on its realized surplus at $\theta = \bar{\theta}$. This asymmetry impacts firms' equilibrium strategies, as we show in Section 4.3.

4.3 | Equilibrium Strategies

When data is shared, expected joint profits depend on whether the regulator accepts or blocks the merger:

$$\begin{aligned} \Pi(s,\alpha) &= (1-\alpha)\pi^A(\bar{\theta}) \\ &\quad + \alpha\, \pi^C(s, \underline{\theta}) - C(s), \quad \text{if the merger is approved,} \\ \Pi_B(s,\alpha) &= (1-\alpha)\pi^C(s, \bar{\theta}) \\ &\quad + \alpha\, \pi^C(s, \underline{\theta}) - C(s), \quad \text{if the merger is blocked.} \end{aligned} \tag{9}$$

Π_B also gives profits in the pool-to-compete equilibrium, so the analysis covers $\sigma \le 1$: firms can share $s \le \sigma$ (separating equilibrium, profits Π) or $s > \sigma$ (pooling, profits Π_B). If firms anticipate that their merger request will be blocked, pool-to-compete is more likely.

Let $\Sigma := \{s : G(s, \bar{\theta}) \ge 0\} = [0, \hat{s}^A]$ be the set of sharing levels that induce approval. Let $s^*_A(\alpha) := \text{argmax}_{s \in \Sigma} \Pi(s, \alpha)$ and $s^*_B(\alpha) := \text{argmax}_{s \notin \Sigma} \Pi_B(s, \alpha)$. If $s^*(\alpha) \in \Sigma$, the regulation is not binding and the firms choose $s^*_A(\alpha) = s^*(\alpha)$. If $s^*(\alpha) > \hat{s}^A$, firms face a choice: follow a "puppy dog" strategy (sharing $\hat{s}^A < s^*(\alpha)$ to stay within the approval threshold and obtain merger clearance) or accept blocking and optimize over Π_B. Firms choose the path of sharing-and-merging if $\Pi(s^*_A(\alpha), \alpha) \ge \Pi_B(s^*_B(\alpha), \alpha)$. Denote

$$\Pi^R_{share}(\alpha) := \max\left\{\Pi(s^*_A(\alpha), \alpha),\ \Pi_B(s^*_B(\alpha), \alpha)\right\}$$

the maximum profits with a regulator. Firms share data only if $\Pi^R_{share}(\alpha) \ge \Pi^R_{noshare}(\alpha)$.

The following lemma characterizes the full partition of equilibrium outcomes under regulation.

Lemma 2. *Under regulation, there exist thresholds α_0, α^R, and α^R_2 with $\alpha_0 \le \alpha^R \le \alpha^R_2 < \alpha_2$ such that*:

i. when $\alpha \in [0, \alpha_0)$, firms merge under incomplete information rather than sharing, and regulation discourages data sharing;

ii. when $\alpha \in [\alpha^R_2, \alpha_2)$, firms compete without sharing (with $\alpha^R_2 < \alpha_2$ when $s^*(\alpha_2) > \hat{s}^A$);

iii. when $\alpha \in (\alpha^R, \alpha^R_2]$ (with $\alpha^R < \alpha^R_2$ if $\Pi^*(\alpha^R) \ge \pi^0$), firms share data and the regulator approves the merger at high synergies, even though a merger with incomplete information would be blocked.

Cases (i) and (ii) identify where regulation strictly discourages sharing: in both, the regulatory constraint forces firms away from data sharing even though sharing would be jointly profitable in the absence of regulation. Case (iii) identifies a constructive role for regulation: by requiring firms to share before merging, the regulator can approve mergers it would otherwise block, thereby expanding the scope for efficient M&As. Figure 3 illustrates how $\Pi^R_{share}(\alpha)$ compares with $\mathbb{E}[\pi^A; \alpha]$ and π^0 across values of α.

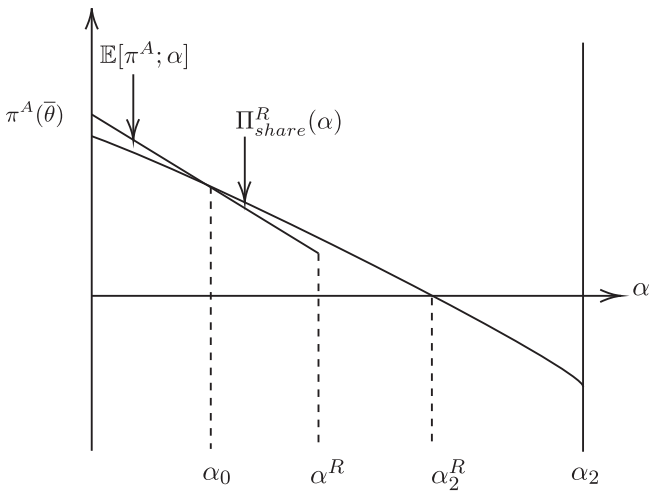


FIGURE 3 | Equilibrium merger gains under regulation.

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Remark 1. Firms share data and compete (rather than merge) only if $\pi^C(s,\overline{\theta}) > \pi^0$ for some s. When this holds, there exist α^B, $\alpha_2^B < \alpha_2$ and $\hat{s}^A(\alpha)$ such that sharing and competing is the equilibrium strategy if and only if $\alpha \in (\alpha^B, \alpha_2^B)$ and $\hat{s}^A < \hat{s}^A(\alpha)$.

The key welfare implication is stated in Proposition 4: by constraining firms' sharing strategies, the regulator reduces consumer surplus whenever it induces less sharing and can improve surplus only when it induces more.

Proposition 4. *Suppose that the regulator authorizes a merger only if it increases consumer surplus.*

i. *If firms share data and request a merger, the amount of data shared and the consumer surplus are smaller than in the absence of a regulator.*
ii. *If firms do not share data because of regulation, expected consumer surplus is smaller than in the absence of a regulator.*
iii. *If firms share data and the merger is blocked, consumer surplus is higher than without a regulator if and only if firms share more data under regulation than without it.*

Cases (i) and (ii) establish that regulation can cause a Pareto reduction: firms earn less and consumers get less, precisely because the regulator is willing to protect consumer surplus. In both cases, the regulator restricts the firms' data-sharing strategies, so they compete less intensively when synergies are low. Case (iii) identifies the configuration in which regulation benefits consumers: when the merger would be blocked regardless, the regulator creates an incentive to share more data and compete more aggressively, raising surplus under competition. Cases (i) and (ii) arise more broadly, so no-regulation can Pareto dominate regulation.

4.4 | Optimal Regulation

The welfare losses identified in Proposition 4 arise because each regulatory instrument targets one stage of the game while distorting incentives in another. Merger control affects sharing incentives at stage 0; data-sharing mandates affect the competitive environment at stage 3; data silo remedies affect post-merger integration but feed back into pre-merger sharing decisions. Designing an optimal policy requires accounting for all of these effects in the cross-stage simultaneously. We analyze each instrument in turn.

4.4.1 | Mandated Data Sharing

Because merger control can reduce data sharing, one natural complement is a mandate requiring firms to share a minimum amount of data. The regulator chooses $s_A \in \Sigma$ to maximize expected consumer surplus conditional on allowing the merger:

$$\mathbb{E}[CS(s_A)] := (1-\alpha)CS^A(\overline{\theta}) + \alpha CS^C(s_A, \underline{\theta}),$$

and chooses $s_B \notin \Sigma$ to maximize expected surplus conditional on blocking:

$$\mathbb{E}[CS(s_B)] := (1-\alpha)CS^C(s_B, \overline{\theta}) + \alpha CS^C(s_B, \underline{\theta}).$$

When the regulator controls s directly, it eliminates the distortion identified in Proposition 4: it can always set $s = s^*(\alpha)$ and prevent the surplus losses that arise when firms strategically reduce sharing to manage merger approval risk. Under H6, the surplus-maximizing mandate is $s = 1$.

Proposition 5. *Regulatory oversight, merger control, and a mandated data-sharing policy yield greater consumer surplus than laissez-faire. Full data sharing is surplus-maximizing, despite potential industry losses, when the regulator is sufficiently oriented toward protecting consumers.*

Mandated data-sharing rules have been enacted in the European Data Act (Art. 35)[22] and in the Digital Markets Act (Art. 61), which requires large digital gatekeepers to provide access, on fair and non-discriminatory terms, to search-generated consumer data. Our analysis suggests a broader role for such rules: when firms are considering a data-driven merger, a mandate can ensure that they acquire sufficient information about synergies before deciding, improving both the efficiency of the merger decision and the intensity of competition if the merger does not proceed.

Consider, for example, Google accessing Fitbit's data under Art. 35 before the merger. Although the Data Act prohibits using accessed data to develop a competing connected product, Google can still use those data in adjacent markets, such as mapping and location services where Fitbit's geo-localization data have cross-market value. This generates a data-feedback loop [16]: access to Fitbit's data increases Google's reach in adjacent markets, which in turn improves its Pixel products. Mandated sharing therefore has a causal impact on firms' ability to learn synergies and on their incentives to merge.

4.4.2 | Merger Control Stringency

A regulator can also vary the stringency of its approval criterion. Let $r \in \mathbb{R}$ parameterize stringency: a merger is approved when $G(s,\overline{\theta}) + r \geq 0$ after sharing, or $\mathbb{E}[G(0,\theta)] + r \geq 0$ without sharing. Positive r denotes leniency; negative r denotes strictness. This approach nests the benchmark case $r = 0$ and allows for a systematic comparison between approval rules, including lenient standards in horizontal merger guidelines.[23]

As r increases, the approval set $\Sigma(r) := \{s : G(s,\overline{\theta}) + r \geq 0\}$ expands and the cutoff $\alpha^R(r)$ increases, making mergers with incomplete information more frequent. When firms share $s_A^*(\alpha)$, a reduction in r tightens the sharing restriction and reduces the consumer surplus. By the continuity of $\Pi_{share}^R(\alpha)$, there exists a threshold r_0 such that firms share even though the merger will be blocked if and only if $r < r_0$: stricter regulation (below r_0) encourages sharing and competition, benefiting consumers even when no merger occurs.

By contrast, when $\alpha < \alpha_0(r)$ firms merge under incomplete information rather than sharing, and when $\alpha \in [\alpha_2^R(r), \alpha_2]$ firms compete without sharing. In both ranges, setting r large enough that $s^*(\alpha)$ lies within $\Sigma(r)$ restores the incentives of the firms to share. The quality competition model in Appendix A.1 illustrates the optimal r explicitly.

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4.4.3 | Merger Remedy: Data Silos

The European Commission has already required data silo remedies in mergers, including Facebook/WhatsApp and Google/Fitbit: the merger is allowed, but the merging parties are prohibited from combining their data sources after the merger [27]. The rationale is to allow efficiency gains from other dimensions of the merger (such as complementary patent portfolios) while limiting the data-driven market dominance that full integration would generate.

We model data silos as follows. With probability γ a silo remedy is required post-merger, in which case the firms' data sets remain separated and the merged firm cannot fully exploit the synergies. Post-silo profits are $\pi^A(s,\overline{\theta})$, where s is the data shared before the merger, with $\frac{\partial \pi^A(s,\overline{\theta})}{\partial s} > 0$: even partial integration is more profitable when more data were shared before the merger. With probability $1-\gamma$ no remedy is required and the merged firm earns $\pi^A(\overline{\theta})$. Expected joint profits under high synergies become:

$$\Pi(s,\alpha) - (1-\alpha)\gamma\left[\pi^A(\overline{\theta}) - \pi^A(s,\overline{\theta})\right]. \tag{10}$$

Proposition 6. *Data silo remedies increase pre-merger data sharing.*

The mechanism is straightforward. A silo remedy reduces expected merger profits by limiting post-merger data integration, which lowers the value of the merger relative to competition. However, it simultaneously raises the value of pre-merger sharing: because $\pi^A(s,\overline{\theta})$ increases with s, sharing more data before the merger improves profits even when silos are imposed. The net effect is that firms have stronger incentives to share data at stage 0, intensifying competition in the event the merger is blocked. This feedback from post-merger regulation to pre-merger competition is a novel effect that standard merger analysis, which focuses on post-merger outcomes only, cannot capture.

The Google/Fitbit acquisition illustrates how silo regulations can also harm consumers after the merger. The data collected via Fitbit are subject to the silo regulation, but data generated through the Pixel Watch is not. Google therefore has incentives to promote Pixel Watch at the expense of Fitbit products, which may explain why Google has progressively discontinued prominent Fitbit features while preserving them on Pixel devices.[24]

5 | Policy Implications

Each regulatory instrument considered in Section 4 targets a specific stage of the game but has unintended effects at other stages, because firms' data-sharing decisions respond to the entire regulatory environment rather than to individual instruments in isolation [1, 28]. The central lesson is that merger control and data regulation cannot be designed independently: ignoring their interaction leads to policies that are internally inconsistent and, in some cases, self-defeating. We derive three concrete recommendations, one for each instrument.

5.1 | Merger Control

The first recommendation concerns how competition authorities assess merger proposals. Our analysis identifies a new source of information that authorities should actively seek: evidence of pre-merger data sharing between the merging parties. Because data sharing requires a monetary transfer, its terms and volume are recorded in both firms' financial statements and are therefore observable during a merger review. When a data-sharing agreement is found, the authority should assess whether it allowed the acquirer to explore the target's data and learn the value of synergies. Such an arrangement is a means to improve merger efficiency, and ignoring it leads to an incomplete picture of the competitive effects of the deal.

The second and more novel recommendation concerns the level of stringency. A striking implication of Proposition 4 is that strict merger control can reduce consumer surplus relative to laissez-faire. The mechanism is indirect: by constraining how much data firms can share and still obtain approval, strict regulation deters pre-merger data sharing, which in turn weakens the competition that the regulator is trying to protect. Lenient merger control, by expanding the set of sharing levels compatible with approval, preserves firms' incentives to share data and can therefore be better for both firms and consumers. This is a novel argument against the traditional case for stringency, and it implies that the optimal level of merger control stringency should account for its effect on pre-merger data sharing, not only its direct effect on post-merger market structure.

5.1.1 | Mandated Data Sharing

The second recommendation concerns data-sharing mandates. Rules of this type, enacted, for instance, in Article 35 of the European Data Act and Article 61 of the Digital Markets Act, are typically designed to promote competition by giving rivals access to data held by incumbents.[25] Our analysis identifies an additional, previously unrecognized effect: mandated sharing affects firms' incentives to learn about synergies before merging and therefore influences both merger frequency and merger efficiency. By ensuring that potential acquirers can access target data before a deal, a mandate can improve the quality of merger decisions, reduce merger failures, and lower the social cost of inefficient acquisitions. Proposition 5 establishes that combining mandatory data sharing with merger control yields a strictly higher consumer surplus than either instrument alone. The policy implication is that data regulators and competition authorities should coordinate: a data-sharing mandate calibrated to the merger context can compensate for the distortions that merger control alone introduces.

This connection is illustrated by the Thomson/Reuters merger, in which the European Commission imposed mandated data sharing as a merger remedy[26] establishing a precedent for using data sharing obligations to manage the competitive effects of data-driven acquisitions. Our results suggest that this type of remedy should be applied more broadly and earlier in the merger review process, rather than as an ex-post condition.

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5.1.1.1 | Data Silo Remedies. The third recommendation concerns post-merger data silo conditions, which the European Commission has imposed in cases including Facebook/WhatsApp and Google/Fitbit: the merger is permitted, but the merging parties are prohibited from combining their data sources. The stated rationale is to allow for efficiency gains from the merger while preventing data-driven market dominance.

Our analysis reveals an unintended consequence that standard merger review usually ignores. A silo remedy reduces expected merger profits by limiting post-merger data integration. However, because pre-merger data sharing improves profits even when silos are later imposed (since $\pi^A(s, \bar{\theta})$ increases with s), the remedy simultaneously raises the incentive to share data before the merger. The net effect, established in Proposition 6, is that firms share more data pre-merger, intensifying competition in the event the merger fails. This is a positive spillover that policy makers do not currently account for when evaluating silo remedies.

The downside is symmetric: by reducing expected merger profitability, silo remedies can deter efficient mergers altogether. If firms anticipate that integration will be blocked, the returns to merging fall, and firms near the margin of indifference between merging and competing may choose not to pursue the deal. This is a social cost that does not appear in standard assessments focused on post-merger market structure. A regulator designing silo conditions should, therefore, weigh the competition benefits of increased pre-merger sharing against the risk of deterring efficient mergers, a trade-off that our model characterizes explicitly in Equation (10).

6 | The Google/Fitbit Merger

The Google/Fitbit acquisition provides unusually detailed evidence for each mechanism the model identifies. The documented timeline shows a credible competitive threat from Google (the Arrow effect), a deliberate partial data migration enabling Google to assess synergies before committing to the deal (the synergy-learning mechanism), a compensating transfer through preferential cloud pricing (the transfer $T(s)$), a conditional acquisition offer consistent with a separating equilibrium, and post-merger product decisions reflecting the asymmetric incentives created by the regulatory silo condition. We trace each of these in turn.

6.1 | Market Context and Strategic Positions

Before the merger, the hardware segment of the health wearable market included Apple, Xiaomi, Samsung, Huawei, and Fitbit. Despite pioneering the market in 2009, Fitbit's share had eroded to approximately 5% of sales volume by the time of the acquisition.[27]

Google occupied a distinctive position: absent from wearable hardware but well-established in adjacent markets through its Google Fit health-tracking platform and Wear OS operating system, already used by Fossil, LG, and others.[28] At the time of the acquisition, both firms understood that Google was simultaneously a potential buyer and a credible competitive entrant, and that the outcome of any partnership would depend on whether their data and algorithms were sufficiently complementary to make the acquisition profitable.

6.2 | The Arrow Effect and the Competitive Threat

A central prediction of the model is that data sharing exposes the sharing firm to competitive losses: by accessing Fitbit's data, Google could improve the quality of its own wearable product and enter the market as a stronger rival (H2, Arrow effect). The Pixel Watch is the documented evidence for this threat.

Google had been developing the Pixel Watch prototype since before 2016.[29] The device was ready to launch around the time of the acquisition and was eventually released in 2022, one year after the deal closed. This timeline confirms that Google was not merely a hypothetical entrant: it had the product, the platform ecosystem (Android, Google Fit, Wear OS), and the development investment to compete directly with Fitbit had the acquisition not proceeded.

Access to Fitbit's health-activity data would have materially strengthened the Pixel Watch, enabling Google to enhance the accuracy of health-monitoring features, refine recommendation and user-interface systems, and exploit complementarities with its Android ecosystem, all of which would have increased Google's competitive appeal and reduced Fitbit's market share. This is precisely the mechanism captured by H2: more shared data raises Google's competitive profits while lowering Fitbit's. Fitbit's awareness of this risk made the sharing decision non-trivial and necessitated the compensating transfer described in Section 6.4.

6.3 | Pre-Merger Data Partnership

In 2018, Fitbit began using Google Cloud Healthcare API to store a subset of its data, while continuing to manage the bulk of its information systems independently.[30] The stated purpose was to facilitate integration between wearable data and electronic health records. However, Google Cloud's press release also noted that the partnership enabled Google to "explor[e] how Google Cloud's machine learning APIs can help them uncover deeper insights," precisely the synergy-learning mechanism our model describes.

Figure 4 illustrates the partial migration structure: Fitbit shares application data with Google Cloud, enabling Google to run experiments and assess synergies, while compensating Fitbit via a monetary transfer.

6.4 | The Logic of Partial Migration

From a technical standpoint, Fitbit's engineers faced a choice in migrating their monolithic MySQL-based application to Google Cloud. An all-at-once migration offered efficiency gains, but risked service outages if compatibility issues arose. Instead, Fitbit opted for progressive shard-by-shard migration, which provided a backup system and, critically, the ability to reverse the process if

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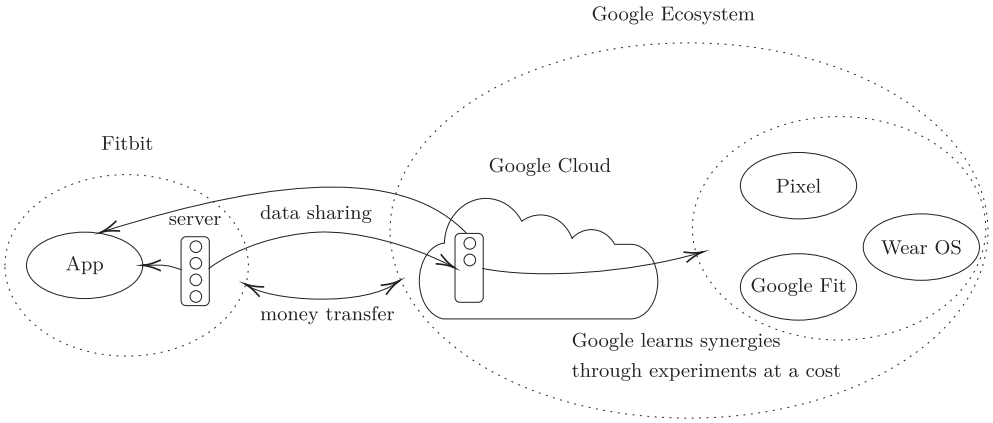


FIGURE 4 | Partial migration of data and learning of synergies.

needed.[31] This is the empirical counterpart of the partial sharing decision $s \in (0, 1)$: Fitbit shared enough data to enable synergy learning while retaining the majority of its information systems independently.

This choice aligns with each component of the theoretical framework. Without any integration, Google could not assess the complementarity of the firms' data assets. Full integration would have resolved this uncertainty but would have exposed Fitbit to expropriation: Google could have used the complete data set to launch a superior Pixel Watch and compete directly, realizing the Arrow effect at full strength.

By sharing only a fraction of its data, Fitbit enabled Google to learn the synergy value while limiting competitive exposure. The model predicts that Google compensates Fitbit for this risk through a transfer $T(s)$. In practice, Google provided cloud services to Fitbit,[32] potentially at preferential rates.

Finally, the model predicts a separating equilibrium: Google proposes an acquisition only when data exploration reveals high synergies, $\theta = \overline{\theta}$. The acquisition offer indeed followed the data partnership, consistent with Google having learned that synergies were sufficiently high to justify the $2.1 billion deal. Specialists recognized this strategic logic at the time (https://www.zdnet.com/article/why-fitbit-could-make-a-good-google-acquisition/Why Fitbit could make a good Google acquisition, ZDNet, May 3, 2018.),[33] and the progressive, reversible nature of the migration provided Fitbit with a credible exit option consistent with the option value in Proposition 2.

6.5 | Post-Merger Integration and Silo Effects

As a condition of regulatory approval, the European Commission required that Google maintain Fitbit's data separate from its other data sources, preventing full post-merger data integration. This is the data silo remedy analyzed in Section 4.4.3. The theoretical prediction of Proposition 6 is that this condition creates asymmetric incentives: because data collected via Fitbit devices is subject to the silo condition while data generated through Pixel Watch is not, Google has a structural incentive to favor Pixel Watch over Fitbit in its product decisions.

The post-merger trajectory of the two product lines is consistent with this prediction. Google has progressively discontinued prominent Fitbit features, including Google Assistant integration, while maintaining and extending equivalent features on Pixel Watch.[34] This is precisely the mechanism of Section 4.4.3: the silo condition makes Fitbit's data constraints binding for one product line but not the other, so Google optimally shifts investment toward the unconstrained product.

7 | Conclusion

This paper identifies two results that jointly reshape how we should think about pre-merger information acquisition and its regulation. First, under general conditions, pre-merger data sharing strictly dominates merging under incomplete information: firms capture an option value that always more than offsets the exploration cost and the competitive loss from sharing, so due diligence in data-driven mergers should include partial data sharing as a standard instrument for learning about complementarities. Second, and more surprisingly, strict merger control can reduce consumer surplus below the laissez-faire level: a consumer-protecting regulator can harm the very consumers it is trying to protect. Together, these two results imply that merger control and data-sharing mandates are complements, not substitutes, and that this combination is the welfare-maximizing policy.

The Google/Fitbit acquisition illustrates each mechanism in practice. The pre-merger data partnership served as a synergy-learning device; the preferential cloud pricing was the transfer compensating Fitbit for its competitive exposure; the acquisition offer followed the partnership by 18 months, consistent with a conditional offer; and the data silo remedy created the asymmetric post-merger incentives the model predicts. The same pattern, a data partnership preceding an acquisition, appeared in the IBM acquisition of The Weather Company, where IBM had previously integrated The Weather Company's data through IBM Cloud to assess complementarities with its IoT analytics platform before proceeding with the deal.[35] These cases suggest that pre-merger data partnerships are a widespread feature of data-driven acquisitions rather than an idiosyncrasy of the Google/Fitbit deal.

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Several extensions remain for future work. The separating equilibrium predicts a testable pattern: among data-driven acquisitions preceded by formal data partnerships, the acquisition price should reflect the synergy level learned during the partnership period, implying a tighter relationship between pre-merger data scope and deal valuation than is observed in acquisitions made without prior data sharing. Testing this prediction would require matched data on partnership terms, transferred data volumes, and acquisition prices, a data set that is feasible to construct from public filings and regulatory disclosures. Two further theoretical directions are also of interest: allowing divestment after inefficient mergers, which would modify the option value when firms can undo a bad deal; and modeling data as time-limited, which would alter the Arrow effect by reducing the competitive threat that shared data poses as it ages.

Acknowledgements

We would like to thank Stefan Bechtold, Andreea Cosnita-Langlais, Jacques Crémer, David Gilo, Jan Krämer, Mathieu Parenti, Pierre Régibeau, Shiva Shekhar, Thibaud Vergé, Patrick Waelbroeck, as well as participants to the 2021 CRESSE conference, the 2022 IIOC conference, the 2023 DISS workshop, the 2024 Conference on Regulators and Regulation in the Digital Era, the 2024 IBEO workshop, the 2024 EARIE conference, the 2024 ECARES workshop, the Paris Seminar on the Digital Economics, and to the LIEN seminar for insightful comments and discussions. This project benefited from financial support from FNRS (Project PDR T.01.47.19) and the European Research Council (under the European Union's Seventh Framework Program (FP7-IDEAS-ERC), ERC Grant Agreement OIO-339950). Previous versions of this work have circulated under the titles "Data-Driven Mergers and Acquisitions with Information Synergies," and "The Sale of Data: Learning Synergies Before M&s." Open access publishing facilitated by Eidgenossische Technische Hochschule Zurich, as part of the Wiley - Eidgenossische Technische Hochschule Zurich agreement via the Consortium Of Swiss Academic Libraries.

Funding

This project benefited from financial support from FNRS (Project PDR T.01.47.19) and the European Research Council (under the European Union's Seventh Framework Program (FP7-IDEAS-ERC), ERC Grant Agreement OIO-339950).

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[2] For 2015–2021, [7] estimate that 30% of digital M&As by large tech firms were data-driven, especially among intensive AI users.

[3] See also https://www.forbes.com/sites/forbestechcouncil/2017/10/19/the-three-reasons-why-tech-ma-deals-fail-to-deliver-value/The Three Reasons Why Tech M&A Deals Fail to Deliver Value, Forbes, October 19, 2017. Examples include America Online/Netscape, Twitter/Vine, Yahoo/Tumblr, and Yahoo/Broadcast.com.

[4] While firms like Google and Facebook can infer the type of data owned by other digital firms, they cannot precisely predict synergies without actual integration and analysis. Unity, for example, suffered substantial losses after misjudging acquired data quality. In 2022, it lost $110 million after training AI algorithms on poor-quality client data integrated into its own datasets (https://www.ibm.com/blog/the-impact-of-bad-data-and-why-observability-is-now-imperative/The Impact of Bad Data and Why Observability is Now Imperative, IBM, June 2, 2022.).

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[9] https://www.zdnet.com/article/why-fitbit-could-make-a-good-google-acquisition/ Why Fitbit could make a good Google acquisition, ZDNet, May 3, 2018.

[10] https://eur-lex.europa.eu/eli/reg/2023/2854Data Act, December 22, 2023.

[11] This framework reflects the empirical timeline of the Google/Fitbit merger: prior to the acquisition, Google did not operate in the hardware segment of the health-wearables industry (its Google Fit platform was predominantly software-based, and the Pixel product line did not yet comprise devices in direct competition with Fitbit). The environment nonetheless encompasses both a regime in which Google is not yet active in the wearable market and a counterfactual regime in which it is an incumbent competitor.

[12] This general framework accommodates an arbitrary number of firms competing with Fitbit. Fitbit's profits can be parameterized by the number of competitors, or more generally by any measure of competitive intensity. For expositional clarity, we omit explicit reference to the number of firms in the profit functions.

[13] Significant examples of past merger proceedings include wearable data related to health (Google/Fitbit), detailed user profiles derived from social media platforms (Facebook/WhatsApp), and traffic and navigation data (Google/Waze).

[14] Our results extend to general probability distributions over continuous support $\theta \in [\underline{\theta}, \overline{\theta}]$. For expositional clarity, we restrict attention to the binary case.

[15] In practice, divestment can follow an acquisition and the model could be extended to allow for it. For example, Nokia acquired Withings in 2016 and divested in 2018 at the request of Withings' previous owner https://www.theverge.com/2018/5/2/17310378/nokia-selling-withings-digital-health-business-eric-carreelNokia is selling its digital health business back to the co-founder of Withings, The Verge, May 2, 2018. However, divestment is harder for data-driven mergers that raise consumer privacy concerns, but such concerns are unlikely to disappear if, after a merger, synergies prove low and firms separate. See https://www.theguardian.com/technology/2019/nov/05/fitbit-google-acquisition-health-data'Tossed my Fitbit in the trash': users fear for privacy after Google buys a company, The Guardian, November 6, 2019.

[16] For data-intensive products, the developer's identity is not neutral: a Google-branded product inherits consumers' privacy concerns, which may lower its valuation after the acquisition.

[17] In practice, Google could also transmit hard information about synergies via virtual data rooms, which disclose verifiable data such as algorithm performance and are routinely used in merger proceedings.

[18] We assume that if an acquisition occurs, Fitbit can infer whether Google explored the data by inspecting Google's financial records and observing the associated costs.

[19] We show in Appendix A.3 that this aligns with Google's expected profits at the beginning of the game.

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[20]When $\alpha = 0, \Pi(s, \alpha) = \pi^A(\overline{\theta}) - C(s)$. Firms share all data ($s^*(0) = 1$) and incur cost $C(1) = 0$, so $\Pi(1) = \pi^A(\overline{\theta})$.

[21]A regulator could also include industry profits in its merger decision, capturing the long-term effect of firms' profits on innovation. Our qualitative results are robust to this alternative rule.

[22]https://eur-lex.europa.eu/eli/reg/2023/2854Data Act, December 22, 2023.

[23]An alternative is for the regulator to internalize the long-term effects of mergers on innovation.

[24]https://www.tomsguide.com/wellness/smartwatches/google-is-slowly-shuttering-fitbit-should-you-still-buy-oneGoogle is slowly killing Fitbit: should you still buy one? Tom's Guide, October 3, 2024.

[25]https://eur-lex.europa.eu/eli/reg/2023/2854Data Act, December 22, 2023.

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[31]As explained by Fitbit's Principal Software Engineer: https://diginomica.com/how-fitbit-moved-its-monolithic-application-google-cloud-platform How Fitbit moved its monolithic application to Google Cloud Platform. Diginomica, August 12, 2020.

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[34]https://www.tomsguide.com/wellness/smartwatches/google-is-slowly-shuttering-fitbit-should-you-still-buy-oneGoogle is slowly killing Fitbit: should you still buy one? Tom's Guide, October 3, 2024. https://www.techradar.com/health-fitness/smartwatches/the-slow-painful-death-of-fitbit-continues-with-google-assistant-the-latest-feature-to-be-axed The slow, painful death of Fitbit continues, with Google Assistant the latest feature to be axed. TechRadar, April 17, 2025.

[35]https://www.prnewswire.com/news-releases/ibm-and-the-weather-company-partner-to-bring-advanced-weather-insights-to-business-300058265.html IBM and The Weather Company Partner to Bring Advanced Weather Insights to Business. PR Newswire, March 31, 2015.

[36]Similar forms of cost function are typical in the econometrics literature where Pearson's chi-squared test is defined as the sum of normalized distances of each observation from the corresponding element of a distribution.

[37]We assume for simplicity that consumers immediately know the product's value. This aligns with our assumption that, when synergies are unknown to Fitbit, the firm can observe the quality of Google's product at the time of competition. In general, consumers can quickly discover their product value before purchasing it through sampling, free download, freemium, ratings, and reviews [29].

[38]Note that this model is isomorphic to a setting where data improves the product quality of Google (and $\overline{\theta} > \underline{\theta} = u$), but merging induces a cost, for instance, administrative or from shock of culture, as we have already explained in the introduction.

[39]This assumes that the merged firm cannot sell a product of quality equal to u in case of low synergies. This effect captures situations where the identity of the firm selling the product is not neutral, which is in line with our narrative where consumers have privacy concerns. If Google poses a threat to their privacy, consumers will have a lower valuation of the product after the acquisition. (See, for instance, https://www.theguardian.com/technology/2019/nov/05/fitbit-google-acquisition-health-data'Tossed my Fitbit in the trash': users fear for privacy after Google buys a company, The Guardian, November 6, 2019.).

[40]See [30] for a micro-foundation of these inverse demand functions.

[41]Proof available upon request.

[42]Since (13) is violated, the right hand side is larger than $\pi^A(\overline{\theta}) - \pi_G^C(s, \overline{\theta})$.

[43]Precisely, we need that $q > \left(\pi^A(\underline{\theta}) - \pi_G^C(s, \underline{\theta}) - \pi_F^C(s, \overline{\theta})\right) / \left(\pi_F^C(s, \underline{\theta}) - \pi_F^C(s, \overline{\theta})\right)$.

[44]In terms of primitives, we have $\alpha^R < \alpha_1$ when $\frac{CS^A(\overline{\theta}) - CS^0}{CS^A(\overline{\theta}) - CS^A(\underline{\theta})} < \frac{\pi^A(\overline{\theta}) - \pi^0}{\pi^A(\overline{\theta}) - \pi^A(\underline{\theta})}$.

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Appendix A

Micro-Founded Applications

We present two micro-founded models to demonstrate the applicability of our reduced-form methodology to classical modes of competition. In the first framework, we examine price competition in the manner of Bertrand, whereas in the second framework, we investigate quantity competition following the Cournot model. Within both models, we establish the validity of the assumptions underlying our primary analysis. We also delineate the optimal regulatory measures in the context of the price competition model.

In these micro-founded models we focus on a market structure where Fitbit is initially a monopolist in the market, and Google can enter only if some of Fitbit's data has been shared. Although this polar market structure plays against merger acceptance, as a merger always results in a monopoly, we show that even in this most conservative setting, there is room for merger control design under which firms have incentives to share data and some mergers are accepted. Both applications can be extended to account for an arbitrary number of firms.

A Price Competition Model Our first micro-foundation is Bertrand competition among firms offering products of different qualities. Before the data is shared, Fitbit sells a product of quality q_F^0 at a price p_F^0, and Google sells a product of quality q_G^0 at a price p_G^0. There is a mass 1 of consumers with quasi-linear utility functions $u(q_i, p_i) = q_i - p_i$. Firms compete à la Bertrand to sell their products, and the firm that wins the market makes profits equal to $\pi_i = p_i$.

At the beginning of the game, only Fitbit can provide positive quality, that is $q_F^0 > 0$, $q_G^0 = 0$. This is consistent with an industry where a monopolist faces a platform that is initially not active in this market. The important element here is that Fitbit initially provides a product of higher quality than Google. Equilibrium prices and profits are $\pi_F^0 = p_F^0 = q_F^0$ and $\pi_G^0 = p_G^0 = 0$.

Data Sharing Assume Fitbit shares $s > 0$, and ignore for now the possibility of a M&A. The exploration cost is $C(s) = \frac{(1-s)^2}{s}$. In this application, we focus on a functional form following a normalized sum of squared deviations to the total amount of data shared corresponding to $s = 1$. The greater the distance to the full set of data, the more costly it is to infer its synergistic value.[36] Decomposing further this functional form, we see that this specific cost captures the reduction in inference costs from obtaining more data through the terms $1 - s$ and $\frac{1}{s}$. As mentioned in the baseline model, these terms capture potential economies of scope and of scale in the inference task. The fact that inferring synergies from a small share of data is very costly is captured by the denominator, as $\lim_{s\to 0} \frac{1}{s} = +\infty$. Conversely, the exploration cost is equal to zero when all data is shared as $1 - s = 0$ when $s = 1$. Finally, $1 - s$ is squared to ensure that the derivative of $C(s)$ is equal to zero at $s = 1$. These different elements combined in $C(s)$ ensure that the cost function satisfies the Inada conditions of our baseline model.

After learning θ, Google can develop a product with quality $q_G(s, \theta) = s\theta$, while Fitbit's product quality remains the same.[37] Representing the value enhancements resulting from data access using such a quality term that directly increases with the amount of data is typical in the literature on data sharing, especially in platform ecosystems. For instance, [1] and [27] use a similar form of increase in product quality when a firm has more data. We augment this approach by allowing the quality term to depend on the value of synergies through parameter θ.

The assumptions of the baseline model remain valid within this framework under the condition $\overline{\theta} > u > 2\underline{\theta}$. By positing $u > \underline{\theta}$, there is a loss of value from low synergies. This aligns with our narrative where consumers might lose utility from privacy concerns when their data is transferred to Google. For example, we can define $\theta := \nu - \mathcal{P}$, where $\nu \in \{\overline{\nu}, \underline{\nu}\}$ is the gain in product quality from sharing data with $\overline{\nu} > \underline{\nu} > u$; and $\mathcal{P}$ represents the privacy losses encountered by consumers, which increase when more data is shared, yielding $\overline{\theta} = \overline{\nu} - \mathcal{P}$ and $\underline{\theta} = \underline{\nu} - \mathcal{P}$.[38] Under this condition, the equilibrium will always be separating.

Consumers purchase the product that yields the highest utility, and Bertrand competition implies that the equilibrium profits of the firms are

$$\pi_F^C(s, \theta) = 0, \quad \pi_G^C(s, \theta) = s\theta - u \text{if } s\theta - u \geq 0,$$
$$\pi_F^C(s, \theta) = u - s\theta, \quad \pi_G^C(s, \theta) = 0 \text{if } s\theta - u \leq 0.$$

The assumptions of the nonparametric model are satisfied with this quality competition model.

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$$\frac{\partial \pi_G^C(s,\theta)}{\partial s} = \theta \geq 0 \geq \frac{\partial \pi_F^C(s,\theta)}{\partial s} = 0 \text{ if } s\theta - u \geq 0,$$
$$\frac{\partial \pi_G^C(s,\theta)}{\partial s} = 0 \geq 0 \geq \frac{\partial \pi_F^C(s,\theta)}{\partial s} = -\theta \text{ if } s\theta - u \leq 0. \quad \text{(H2)}$$

Assuming $u > \underline{\theta}$, low synergies make competitive payoffs equal to $\pi_F^C(s,\underline{\theta}) = u - s\underline{\theta}$ and $\pi_G^C(s,\underline{\theta}) = 0$, ensuring (H3) is satisfied:

$$\frac{\partial \pi^C(s,\underline{\theta})}{\partial s} = -\underline{\theta} < 0. \quad \text{(H3)}$$

The complementarity between data and synergies for Google also takes place in this setting:

$$\frac{\partial \pi_G^C(s,\theta)}{\partial s \partial \theta} = 0 \text{ if } s\theta - u \leq 0, \qquad \frac{\partial \pi_G^C(s,\theta)}{\partial s \partial \theta} = 1 \text{ if } s\theta - u \geq 0. \quad \text{(H4)}$$

Finally, the competitive profits of Fitbit and Google with sharing and high synergies are:

$$\pi^C(s,\overline{\theta}) = u - s\overline{\theta} \text{ if } s\overline{\theta} - u \leq 0,$$
$$\pi^C(s,\overline{\theta}) = s\overline{\theta} - u \text{ if } s\overline{\theta} - u \geq 0.$$

M&A When firms merge, the merged entity sells as a monopolist a product of quality equal to $q_G(1,\overline{\theta}) = \overline{\theta}$ if synergies are high and to $q_G(1,\underline{\theta}) = \underline{\theta}$ if synergies are low.[39]

Alternatively, we can assume that the merged firm sells the product with the highest quality between θ and u, that is, $\overline{\theta}$ if the synergies are high and u if synergies are low. Both approaches are equivalent by assuming that there is a positive cost to merge, even slightly above zero.

As we have assumed that $\overline{\theta} > u$ and $u > 2\underline{\theta}$, Google and Fitbit are willing to merge only when synergies are high and we recover the option value of the baseline model:

$$\pi^A(\overline{\theta}) = \overline{\theta} > \pi^C(s,\overline{\theta}) = \max\{u - s\overline{\theta}, s\overline{\theta} - u\},$$
$$\pi^A(\underline{\theta}) = \underline{\theta} < u - s\underline{\theta}. \quad \text{(H5)}$$

The price of the acquisition is equal to:

$$p^A(s) = \begin{cases} p^*(s) = \max\{u - \overline{\theta}s, 0\} \\ +\mu(\overline{\theta} - \max\{u - \overline{\theta}s, \overline{\theta}s - u\}) & \text{if } p^*(s) \geq \underline{\theta} \\ \overline{\theta} - \max\{0, \overline{\theta}s - u\} & \text{if } p^*(s) \leq \underline{\theta}. \end{cases}$$

Equilibrium Data Sharing The expected profit of Google purchasing s from Fitbit is:

$$(1-\alpha)(\overline{\theta} - u) - \alpha\underline{\theta}s - C(s).$$

By concavity of this expression, the equilibrium amount of data shared is unique and satisfies

$$\alpha\underline{\theta} = -C'(s^*(\alpha)) = \frac{1 - s^*(\alpha)^2}{s^*(\alpha)^2} \Rightarrow s^*(\alpha) = \sqrt{\frac{1}{1+\alpha\underline{\theta}}}.$$

Consumer Surplus The surplus of consumers is equal to zero if firms do not share data or if they merge. If firms share data and compete, the consumer surplus equals $\min\{u, s\theta\}$. This weakly increases with s, and is linear on $[0, \frac{u}{\theta}]$ and $[\frac{u}{\theta}, 1]$.

Regulation A merger with incomplete information does not change consumer surplus:

$$\mathbb{E}[G(0,\theta)] = 0$$

and a M&A is always accepted under incomplete information, since a regulator clears M&As only if they increase the surplus of consumers. This is a polar case where a merger does not induce any gain for consumers under incomplete information.

When firms share s data, a M&A in case of high synergies is detrimental to consumers:

$$G(s,\overline{\theta}) = -\max\{u, s\overline{\theta}\}.$$

This function is negative, and the merger is never approved after data has been shared. Hence, the regulator discourages firms from sharing data. Firms prefer to merge under incomplete information or share data and compete. In the last case, firms anticipate profits equal to:

$$(1-\alpha)(\max\{u - s\overline{\theta}, s\overline{\theta} - u\}) + \alpha(u - s\underline{\theta}) - C(s)$$

For sharing to be profitable, it is necessary that $s\overline{\theta} > u$. Moreover, for sharing to dominate competition without sharing, we must have:

$$(1-\alpha)(s\overline{\theta} - 2u) - \alpha s\underline{\theta} - C(s) > 0.$$

We can see that a sufficient condition for sharing and competing to be a profitable strategy is when the above condition is satisfied for $s = 1$. In this case, the inequality writes:

$$\overline{\theta} > \frac{\alpha}{1-\alpha}\underline{\theta} + 2u.$$

Under this sufficient condition, we see that the presence of the regulator does not necessarily discourage firms from sharing, since their profits in case synergies are high can be significantly greater than those without sharing. In contrast, when $\overline{\theta} < 2u$, $(1-\alpha)(s\overline{\theta} - 2u) - \alpha s\underline{\theta} - C(s)$ will always be negative and firms will not share data under this sufficient condition.

Optimal Stringency Profits in case of sharing and competing are

$$\Pi_B(s,\alpha) = (1-\alpha)(s\overline{\theta} - u) + \alpha(u - s\underline{\theta}) - C(s)$$

which are maximized for

$$s_B^*(\alpha) = \begin{cases} 1 & \text{if } \alpha\underline{\theta} \leq (1-\alpha)\overline{\theta} \\ \sqrt{\frac{1}{1-(1-\alpha)\overline{\theta}+\alpha\underline{\theta}}} & \text{if } \alpha\underline{\theta} \geq (1-\alpha)\overline{\theta} \end{cases} \quad (11)$$

For any α, there exists $\hat{\theta}$ ($> 2u$) such that firms share and compete if $\overline{\theta} > \hat{\theta}$ and do not share otherwise. Hence, the optimal degree of stringency depends on $\overline{\theta}$. If $\overline{\theta} > \hat{\theta}$, the regulator sets $r = 0$ and the surplus is high with firms sharing data and competing. If $\overline{\theta} \leq \hat{\theta}$, the firms do not share and the regulator can induce them to share by increasing r. Specifically, a M&A will be accepted if

$$G(s,\overline{\theta}) + r \geq 0 \Rightarrow r - \max\{u, s\overline{\theta}\} \geq 0$$

Consumer surplus increases when firms share more data, anticipating that they can merge if synergies are high. A regulator can promote such data sharing among firms by implementing a more lenient regulation captured by $r > 0$. Doing so, the regulator initially provides firms with incentives to share data $\hat{s}^A$, which increases with r. For $r \geq \max\{u, s^*(\alpha)\overline{\theta}\}$, $\hat{s}^A$ is higher than $s^*(\alpha)$, leading firms to share the optimal amount of data $s^*(\alpha)$. Consequently, an optimal regulation has a degree of leniency $r \geq \max\{u, s^*(\alpha)\overline{\theta}\}$.

A Quantity Competition Model Our second micro-foundation is Cournot competition. Firms offer products of quality q_F, q_G and compete à la Cournot by setting quantities x_F and x_G to sell their products, and, denoting total output $X = x_F + x_G$, firms have the following inverse demand functions:[40]

$$P_F = u - X, \quad P_G = q_G - X.$$

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We normalize production costs to zero, and firms make profits:

$$\pi_F^0 = P_F x_F, \quad \pi_G^0 = P_G x_G.$$

Before data is shared, Fitbit's product is of quality u, and Google's product is of quality $q_G^0 = 0$.

Data Sharing Suppose that Fitbit shares $s > 0$, and, for now, let us ignore the possibility of a M&A. As in the Bertrand specification, if Google invests $C(s) = \frac{(1-s)^2}{s}$ and learns θ, it can develop a product of quality $q_G(s,\theta) = s\theta$, while the quality of the product of Fitbit does not change. If Google does not invest $C(s)$, its product quality is zero. As in the Bertrand competition case, this is a typical form of quality improvement in the literature which we augment using the uncertainty over the value of θ.

The main hypotheses of the baseline model hold when $\overline{\theta} > 2\sqrt{u^2+u}$ and $u > \underline{\theta}$. In particular, the equilibrium will always be separating. Firms make the following competitive profits with data sharing:

$$\pi_F^C(s,\theta) = (u - X)x_F,$$
$$\pi_G^C(s,\theta) = (s\theta - X)x_G.$$

Standard analysis allows us to characterize the equilibrium outputs:

$$\begin{aligned}
&x_F = \frac{u}{2}, && x_G = 0 && \text{if } u > 2s\theta\\
&x_F = \frac{2u - s\theta}{3}, && x_G = \frac{2s\theta - u}{3} && \text{if } 4u \geq 2s\theta \geq u\\
&x_F = 0, && x_G = \frac{s\theta}{2} && \text{if } s\theta \geq 2u.
\end{aligned}$$

In turn, the profits of the firms are:

$$\begin{aligned}
&\pi_F^{C*}(s,\theta) = \frac{u^2}{4}, && \pi_G^{C*}(s,\theta) = 0 && \text{if } u > 2s\theta,\\
&\pi_F^{C*}(s,\theta) = \frac{1}{9}(2u - s\theta)^2, && \pi_G^{C*}(s,\theta) = \frac{1}{9}(2s\theta - u)^2 && \text{if } 4u \geq 2s\theta \geq u,\\
&\pi_F^{C*}(s,\theta) = 0, && \pi_G^{C*}(s,\theta) = \frac{(s\theta)^2}{4} && \text{if } s\theta \geq 2u.
\end{aligned}$$

These Cournot profits satisfy the assumptions of our main model. The Arrow effect holds

$$\frac{\partial \pi_G^C(s,\underline{\theta})}{\partial s} = \max\{0, 4s\underline{\theta}(2s\underline{\theta} - u)\} \geq 0 \geq \frac{\partial \pi_F^C(s,\underline{\theta})}{\partial s} = \min\{0, 2\theta(s\underline{\theta} - 2u)\}. \tag{H2}$$

The competitive payoffs are equal to:

$$\begin{aligned}
&\pi^C(s,\theta) = \frac{u^2}{4} && \text{if } u > 2s\theta,\\
&\pi^C(s,\theta) = \frac{1}{9}\left(5s^2\theta^2 - 8s\theta u + 5u^2\right) && \text{if } 4u \geq 2s\theta \geq u,\\
&\pi^C(s,\theta) = \frac{(s\theta)^2}{4} && \text{if } s\theta \geq 2u.
\end{aligned}$$

These profits decrease with s and (H3) is satisfied:

$$\begin{aligned}
&\frac{\partial \pi^C(s,\underline{\theta})}{\partial s} = 0 && \text{if } u > 2\underline{\theta}s,\\
&\frac{\partial \pi^C(s,\underline{\theta})}{\partial s} = \frac{2}{9}\,\underline{\theta}\,(5s\underline{\theta} - 4u) \leq 0 && \text{if } 2\underline{\theta}s \geq u.
\end{aligned} \tag{H3}$$

The data-synergies complementarity for Google's profits also takes place:

$$\frac{\partial^2 \pi_G^C(s,\theta)}{\partial s \partial \theta} = \begin{cases} 0 & \text{if } u > 2s\theta,\\ \frac{4}{9}(4s\theta - u) & \text{if } 4u \geq 2s\theta \geq u,\\ s\theta & \text{if } s\theta \geq 2u. \end{cases} \tag{H4}$$

Finally, taking the second-degree derivative of the sum of Fitbit and Google's payoffs with high synergies, we can see that these profits are quasi-concave in s:

$$\begin{aligned}
&\frac{\partial^2 \pi^C(s,\overline{\theta})}{\partial s^2} = 0 && \text{if } u > 2s\theta,\\
&\frac{\partial^2 \pi^C(s,\overline{\theta})}{\partial s^2} = \frac{10\,\overline{\theta}}{9} > 0 && \text{if } 4u \geq 2s\theta \geq u,\\
&\frac{\partial^2 \pi^C(s,\overline{\theta})}{\partial s^2} = 0 && \text{if } s\theta \geq 2u.
\end{aligned}$$

M&A When firms merge, the merged entity sells as a monopolist a quality product equal to $q_G(1,\overline{\theta}) = \overline{\theta}$ if synergies are high and to $q_G(1,\underline{\theta}) = \underline{\theta}$ if synergies are low. As in the price competition model, we could equivalently assume that the merged firm sells a quality product u in the case of low synergies, but there is a cost to merge.

The profits of the merged company are $\pi^A(\theta) = \max_x(\theta - x)x$. Hence, the optimal output is $x^M(\theta) = \frac{\theta}{2}$, so that the profits after the merger are

$$\pi^A(\theta) = \frac{1}{4}\theta^2.$$

To show that a merger is not profitable with low synergies, it is necessary and sufficient to prove that a merger yields lower profits than competition with the minimizing value of s. As $\pi^C(s,\underline{\theta})$ decreases with s, it is the lowest for $s = 1$. With this amount of data shared, a merger is detrimental with low synergies when $\frac{10u}{11} > \underline{\theta}$, which is implied by our assumption that $u > 2\underline{\theta}$.

In contrast, if a merger with high synergies is profitable for the value of s that yields the highest competitive profits $\pi^C(s,\overline{\theta})$, then mergers are always profitable. As $\pi^C(s,\overline{\theta})$ is convex, it is maximized for $s = 0$ or for $s = 1$. In both cases, simple analysis allows us to verify that a merger is profitable as we have assumed $\overline{\theta} > u$. Overall, Google and Fitbit are willing to merge only when synergies are high and we recover the option value of the baseline model:

$$\begin{aligned}
&\pi^A(\overline{\theta}) = \frac{1}{4}\overline{\theta}^2 > \pi^C(s,\overline{\theta}),\\
&\pi^A(\underline{\theta}) = \frac{1}{4}\underline{\theta}^2 < \pi^C(s,\underline{\theta}).
\end{aligned} \tag{H5}$$

Equilibrium Data Sharing The expected profit of Google purchasing s from Fitbit is:

$$(1-\alpha)\frac{1}{4}(\overline{\theta}^2 - u^2) + \alpha\frac{1}{9}\left(5s^2\underline{\theta}^2 - 8s\underline{\theta}u + 5u^2\right) - C(s).$$

The second-degree derivative of this profits with respect to s is equal to $10\,\alpha\,\underline{\theta}^2 - \frac{2}{s^3}$, and is thus negative for all values of s and α as long as $\underline{\theta} > \frac{1}{\sqrt{5}}$. In this case, the equilibrium amount of data shared is unique and satisfies

$$\frac{2}{9}\,\alpha\,\underline{\theta}(5\,s^*(\alpha)\underline{\theta} - 4u) = C'(s^*(\alpha)).$$

Consumer Surplus As usual with Cournot, total output is a sufficient statistic for consumer surplus, and we have $CS = \frac{X^2}{2}$.[41] Baseline competition yields a surplus equal to $CS^0 = \frac{u^2}{8}$. After a merger when synergies are high, consumer surplus is equal to $CS^A(\overline{\theta}) = \frac{\overline{\theta}^2}{8}$, while it is equal to $CS^A(\underline{\theta}) = \frac{\underline{\theta}^2}{8}$ in case of low synergies. If firms share data and compete, the total production equals $\frac{1}{3}(s\theta + u)$, which weakly increases with s, and in turn, so does the surplus of the consumer. This ensures that H6 is satisfied. Assumption (H7) holds as $\overline{\theta} > \frac{2u}{3} > \underline{\theta}$.

$$CS^A(\overline{\theta}) = \frac{\overline{\theta}^2}{8} > CS^0 = \frac{u^2}{8} > CS^A(\underline{\theta}) = \frac{\underline{\theta}^2}{8}. \tag{H7}$$

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Finally, (H8) is also satisfied:

$$CS^C(1,\overline{\theta}) = \frac{1}{18}(\overline{\theta}+u)^2 > CS^A(\overline{\theta}) = \frac{\overline{\theta}^2}{8} \qquad \text{if } 2u > \overline{\theta},$$
$$CS^C(1,\overline{\theta}) = CS^A(\overline{\theta}) = \frac{\overline{\theta}^2}{8} \qquad \text{if } 2u \le \overline{\theta}. \qquad \text{(H8)}$$

To keep the discussion concise we leave the analysis of the equilibrium under regulation available upon request, but it is clear that, as all the baseline assumptions are satisfied, the general results of the main model hold also in this micro-founded application.

Proof of Proposition 1

Separating Equilibrium Suppose that $\theta = \overline{\theta}$. In equilibrium, Fitbit and Google "share" the belief that $\theta = \overline{\theta}$, in which they respectively get p^A and $\pi^A(\overline{\theta}) - p^A$. The frontier of the set of allocations to respectively Fitbit and Google (u_F, u_G) that dominate the threat point $(\pi_F^C(s,\overline{\theta}), \pi_G^C(s,\overline{\theta}))$ is obtained by varying p^A in the interval

$$D := [\pi_F^C(s,\overline{\theta}), \pi^A(\overline{\theta}) - \pi_G^C(s,\overline{\theta})],$$

with D nonempty by assumption $\pi^A(\overline{\theta}) > \pi^C(s,\overline{\theta})$. However, Google may be tempted to offer acquisition at price $p^A \in D$ even in state $\underline{\theta}$. This will not happen whenever Google's payoff from acquisition $\pi^A(\underline{\theta}) - p^A$ is smaller than its equilibrium payoff $\pi_G^C(s,\underline{\theta})$ in state $\underline{\theta}$. Hence, incentive compatibility requires that $p^A \ge \pi^A(\underline{\theta}) - \pi_G^C(s,\underline{\theta})$.

Anticipating the incentive compatibility problem, at the time of acquisition, Fitbit, and Google bargain over the constrained set

$$\begin{aligned} D^* &:= D \cap [\pi^A(\underline{\theta}) - \pi_G^C(s,\underline{\theta}), \infty] \\ &= \left[\max\{\pi_F^C(s,\overline{\theta}), \pi^A(\underline{\theta}) - \pi_G^C(s,\underline{\theta})\}, \pi^A(\overline{\theta}) - \pi_G^C(s,\overline{\theta})\right]. \end{aligned} \qquad (12)$$

Because $\pi^A(\overline{\theta}) > \pi^C(s,\overline{\theta})$, a necessary and sufficient condition for a separating equilibrium is then that

$$\pi^A(\overline{\theta}) - \pi^A(\underline{\theta}) \ge \pi_G^C(s,\overline{\theta}) - \pi_G^C(s,\underline{\theta}). \qquad (13)$$

Equivalently, when synergies increase, the profits under acquisition must increase by more than the profit to Google under competition. The generalized Nash bargaining outcome is obtained as the solution to

$$\max_{p^A \in D^*} (p^A - \pi_F^C(s,\overline{\theta}))^{\mu} (\pi^A(\overline{\theta}) - p^A - \pi_G^C(s,\overline{\theta}))^{1-\mu}$$

Note that $D^* = D$ whenever $\pi^A(\underline{\theta}) - \pi_G^C(s,\underline{\theta}) \le \pi_F^C(s,\overline{\theta})$. In this case, the solution is the same as without the incentive problem, that is

$$p^*(s) = \pi_F^C(s,\overline{\theta}) + \mu(\pi^A(\overline{\theta}) - \pi^C(s,\overline{\theta})).$$

More generally, if $p^*(s) \in D^*$, the solution to the constrained problem is $p^A(s) = p^*(s)$. Otherwise the solution is at the lower bound of D^*, that is at $p^A(s) = \pi^A(\overline{\theta}) - \pi_G^C(s,\overline{\theta})$.

Pooling-to-Merge Equilibrium If pooling to merge is an equilibrium, ex-ante, Google has a payoff of $\mathbb{E}[\pi^A(\theta)] - p^A(s) - C(s)$ and Fitbit of $p^A(s)$. This is dominated by early acquisition at price p^A since Google has a payoff of $\mathbb{E}[\pi^A(\theta)] - p^A$ and saves $C(s)$.

Pooling-to-Compete Equilibrium Suppose that Google is not expected to offer acquisition. At this stage $C(s)$ has been sunk by Google and Fitbit has imperfect information about θ and expects a profit of $\mathbb{E}[\pi_F^C(s,\theta)]$. Suppose first that the set D^* in (12) is non-empty. If Google deviates in state $\overline{\theta}$ and offers a price p^A such that $p^A \in D^*$: then, Google is better off than in the pooling outcome while type $\underline{\theta}$ would be worse off offering acquisition. Using the Never a Weak Best Response (NWBR) refinement (e.g., [31]), Fitbit should put a probability one on the state being $\overline{\theta}$ when Google offers to acquire Fitbit at price $p^A \in D^*$. Hence pooling-to-compete is not stable when D^* is non-empty.

Suppose now that D^* is empty. In order for the pooling-to-compete strategy to be stable, neither $\overline{\theta}$ or $\underline{\theta}$ can benefit from offering acquisition, or acquisition is refused by Fitbit. Since D^* is empty, any beneficial deviation by offering a price p^A by $\overline{\theta}$ is also beneficial by $\underline{\theta}$. The NWBR criterion does not put restrictions on Fitbit's beliefs in this out-of-equilibrium strategy. Let q be the belief that Fitbit assigns to $\underline{\theta}$ out-of-equilibrium that is beneficial to both $\underline{\theta}, \overline{\theta}$; stability requires that whenever acquisition is profitable for Google, that is when $p^A > \pi^A(\underline{\theta}) - \pi_G^C(s,\underline{\theta})$, Fitbit prefers to reject the offer, that is that $p^A < \mathbb{E}[\pi_F^C(s,\theta)|q]$. Hence, we need[42]

$$q\pi_F^C(s,\underline{\theta}) + (1-q)\pi_F^C(s,\overline{\theta}) > \pi^A(\underline{\theta}) - \pi_G^C(s,\underline{\theta}). \qquad (14)$$

If $\pi_F^C(s,\underline{\theta}) \le \pi_F^C(s,\overline{\theta})$, (14) holds for any q by our assumption that $\pi^A(\underline{\theta}) - \pi^C(s,\underline{\theta}) < 0$. If $\pi_F^C(s,\underline{\theta}) \ge \pi_F^C(s,\overline{\theta})$, condition (14) holds whenever q is large enough.[43]

i. Suppose that condition (13) holds. Then, after data exploitation, the unique equilibrium is separation at acquisition price $p^A(s)$ in Proposition 1.

ii. Suppose that condition (13) does not hold. Then, a pooling-to-compete continuation equilibrium exists.

The Data Shared Maximizes Google's Profits

We note $u_G(s,\alpha)$ the expected value of Google purchasing data s from Fitbit and exploring, net of the non-sharing payoff π_G^0:

$$\begin{aligned} u_G(s,\alpha) :=\ & \overbrace{(1-\alpha)(\pi^A(\overline{\theta}) - p^A(s))}^{\text{Google's profits if } \overline{\theta} \text{ and acquires Fitbit}} + \overbrace{\alpha\, \pi_G^C(s,\underline{\theta})}^{\text{Google's profits if } \underline{\theta}} - \pi_G^0 - C(s) \\ & \underbrace{- (\pi_F^0 + \max\{\mu\big(\mathbb{E}[\pi^A;\alpha] - \pi^0\big), 0\} - (1-\alpha)p^A(s) - \alpha\, \pi_F^C(s,\underline{\theta}))}_{\text{Price of data } T(s)} \\ =\ & \Pi(s,\alpha) - \pi^0 - \max\{\mu\big(\mathbb{E}[\pi^A;\alpha] - \pi^0\big), 0\} \end{aligned} \qquad (15)$$

where $\Pi(s,\alpha)$ is the ex-ante total profits of Fitbit and Google if s is shared before the acquisition

$$\Pi(s,\alpha) := (1-\alpha)\pi^A(\overline{\theta}) + \alpha\ \pi^C(s,\underline{\theta}) - C(s). \qquad (16)$$

Proof of Lemma 2 and Remark 1

Firms Merge Under Incomplete Information Instead of Sharing When α is close to 0, a M&A is accepted under incomplete information. On the contrary, firms are constrained on their sharing strategy: the optimal amount of data shared without the regulator when α equals zero is $s^*(0) = 1$ (see (4)), but the regulator blocks such a M&A since $G(1,\overline{\theta}) = CS^A(\overline{\theta}) - CS^C(1,\overline{\theta})$ is below zero (see (H8)). Hence, for small values of α, the presence of the regulator lowers the firms' profits with sharing, but not those if they merge under incomplete information.

In the absence of regulation, the firms' profits for a M&A under incomplete information are arbitrarily close to those with data sharing, and firms prefer to merge under incomplete information instead of sharing when there is a regulator for small values of α. There, regulation discourages firms from sharing. Formally, there exists $\alpha_0 \in (0,1]$ such that firms prefer to merge under incomplete information instead of sharing when there is a regulator for α below α_0.

Firms Cannot Merge Under Incomplete Information but Merge After Sharing Consider now the decision of the regulator to allow

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a M&A under incomplete information. We have shown that M&As are cleared under incomplete information when α is below $\alpha^R = \frac{CS^A(\overline{\theta})-CS^0}{CS^A(\overline{\theta})-CS^A(\underline{\theta})}$. For CS^0 sufficiently close to $CS^A(\overline{\theta})$, this threshold is lower than α_1, and mergers under incomplete information are blocked by the regulator when $\alpha \in [\alpha^R, \alpha_1)$, even though they are more profitable than competing for the firms.[44]

In this case, firms can still induce the regulator to allow the M&A by sharing data. Indeed, if $s^*(\alpha^R)$ is smaller than $\hat{s}^A$, firms share $s^*(\alpha^R)$ data and the merger is approved when synergies are high. If $s^*(\alpha^R)$ is greater than $\hat{s}^A$, firms share data and merge with high synergies if

$$\Pi(\hat{s}^A, \alpha^R) = (1-\alpha^R)\pi^A(\overline{\theta}) + \alpha^R\ \pi^C(\hat{s}^A, \underline{\theta}) - C(\hat{s}^A) \geq \pi^0.$$

In other words, when $\alpha \in [\alpha^R, \alpha_1)$ the firms can ensure that a M&A takes place when synergies are high by exploring the data as long as $\Pi(s_A^*(\alpha), \alpha) \geq \pi^0$. This implies that the surplus gains from a M&A will be high too.

Firms Compete Instead of Sharing When α is close to α_2, the profits after sharing without regulation are close to π^0. If a M&A with data sharing is blocked at α_2, firms can induce the regulator to accept the merger by sharing $\hat{s}^A < s^*(\alpha_2)$, but doing so lowers their profits below π^0. Hence, by exerting a constraint on the strategies of the firms, the regulator can also induce them not to share data and to compete instead. Formally, when $G(s^*(\alpha_2), \overline{\theta}) \leq 0$, there exists $\alpha_2^R < \alpha_2$ so that firms prefer to compete instead of sharing when there is a regulator for $\alpha \in [\alpha_2^R, \alpha_2)$.

Sharing and Competing Can Be the Firms' Equilibrium Strategy When it yields greater profits than (*i*) merging under incomplete information; (*ii*) sharing and have the M&A accepted; (*iii*) and than competing without sharing.

Sharing and Competing Vs. Merging Under Incomplete Information Sharing and competing will yield higher profits than a merger under incomplete information if $\Pi_B(s_B^*(\alpha), \alpha)$ is greater than $\mathbb{E}[\pi^A; \alpha]$. Consider the difference between both profit functions:

$$\Pi_B(s,\alpha) - \mathbb{E}[\pi^A;\alpha] = (1-\alpha)\underbrace{\left(\pi^C(s,\overline{\theta}) - \pi^A(\overline{\theta}))\right)}_{<0\ (H5)} + \alpha\underbrace{\left(\pi^C(s,\underline{\theta}) - \pi^A(\underline{\theta})\right)}_{>0\ (H5)} - C(s)$$

For $s = 1$, the exploration cost equals zero, and this difference is positive for α greater than a threshold α^B. Hence, this difference will also be positive for $s_B^*(\alpha)$ data shared in this case. This implies that sharing and competing yields higher profits than merging under incomplete information for α high enough.

Sharing and Competing Vs. Sharing and Merging When Synergies Are High $\Pi_B(s_B^*(\alpha), \alpha)$ will be greater than $\Pi(\hat{s}^A, \alpha)$ if $\hat{s}^A$ is small enough. Indeed, for $\hat{s}^A = 1$ all mergers are accepted under high synergies as $s^*(\alpha) \leq \hat{s}^A$. On the contrary, sharing $\hat{s}^A$ is not a profitable strategy when it is close to zero since the exploration cost will be high. Hence, for any value of α, there exists $\hat{s}^A(\alpha)$ such that $\Pi(\hat{s}^A(\alpha), \alpha) = \Pi_B(s_B^*(\alpha), \alpha)$ if $s_B^*(\alpha) > \hat{s}^A(\alpha)$. The existence of $\hat{s}^A(\alpha)$ is guaranteed since the value of $\hat{s}^A$ is determined by the relation $CS^C(\hat{s}^A, \overline{\theta}) = CS^A(\overline{\theta})$, where $CS^A(\overline{\theta})$ can take any value as long as conditions (H7) and (H8) are satisfied.

Thus, when $\hat{s}^A \leq \hat{s}^A(\alpha)$, regulation exerts a strong constraint on the strategies of the firms, up to a point where sharing and having the M&A blocked is more profitable for the firms than sharing less data to have the M&A accepted. This strong regulatory constraint results from a sharp increase of consumer surplus with s when firms compete, such that firms must share few data, otherwise a M&A will be detrimental to consumers and will be blocked by the regulator.

Competing Vs. Sharing and Competing Consider $\alpha \in (\alpha^B, \alpha_2)$ and $\hat{s}^A < \hat{s}^A(\alpha)$ defined above, such that sharing and competing dominates sharing and merging, and mergers under incomplete information are blocked. In this case, sharing s and competing can also be more profitable than competing without sharing if the following difference is positive.

$$\Pi_B(s,\alpha) = (1-\alpha)\left(\pi^C(s,\overline{\theta}) - \pi^0\right) + \alpha\underbrace{\left(\pi^C(s,\underline{\theta}) - \pi^0\right)}_{<0\ (H3)} - C(s)$$

As profits with sharing are below π^0 when firms are constrained, sharing and competing will dominate competition for $\alpha < \alpha_2^B < \alpha_2$. This is illustrated by our quality competition rationale.

Proof of Proposition 4

At stage 0, the expected surplus when $s^*(\alpha)$ data is shared without merger control is:

$$\mathbb{E}[CS^{no}] := (1-\alpha)CS^A(\overline{\theta}) + \alpha CS^C(s^*(\alpha), \underline{\theta}).$$

When firms share $\hat{s}^A < s^*(\alpha)$ to have the merger accepted by the regulator, the expected surplus at the beginning of the game depends on the realization of θ. If synergies are high with prob. $1-\alpha$, firms ask for a M&A, which is cleared by the regulator, and surplus equals $CS^A(\overline{\theta})$. If synergies are low with prob. α, firms compete with $\hat{s}^A$ data shared and surplus equals $CS^C(\hat{s}^A, \underline{\theta})$. The expected surplus with sharing at the beginning of the game is:

$$\mathbb{E}[CS(\hat{s}^A)] := (1-\alpha)CS^A(\overline{\theta}) + \alpha CS^C(\hat{s}^A, \underline{\theta}).$$

Hence, regulation reduces surplus if the following difference is negative:

$$\mathbb{E}[CS(\hat{s}^A)] - \mathbb{E}[CS^{no}] = \alpha(CS^C(\hat{s}^A, \underline{\theta}) - CS^C(s^*(\alpha), \underline{\theta})) < 0.$$

This term is negative since $\hat{s}^A$ is smaller than $s^*(\alpha)$. Hence, the presence of the regulator reduces both consumer surplus and firms' profits.

When firms merge under incomplete information because of the regulator, the expected surplus is $\mathbb{E}[CS^A(\theta)]$, and the variations in surplus due to regulation are equal to:

$$\mathbb{E}[CS^A(\theta)] - \mathbb{E}[CS^{no}] = \alpha(CS^A(\underline{\theta}) - CS^C(s^*(\alpha), \underline{\theta})) < 0.$$

Consumer surplus unilaterally decreases because of the regulator. Consumers lose since firms do not compete with data when synergies are low. Moreover, firms also lose as they no longer share data, even though this would be the unconstrained optimum for the industry.

When firms prefer to compete because of the regulator, consumer surplus is CS^0. The variations of surplus due to the presence of the regulator in this case are equal to:

$$CS^0 - \mathbb{E}[CS^{no}] = CS^0 - (1-\alpha)CS^A(\overline{\theta}) - \alpha CS^C(s^*(\alpha), \underline{\theta}) < 0.$$

In this last case again, the presence of the regulator reduces consumer surplus. Indeed, surplus if firms share data is either realized under a merger with high synergies, or under competition with data shared if synergies are low. In both cases, the resulting surplus is greater than in the baseline competitive mode without sharing.

The presence of the regulator increases surplus if firms share more data. When firms share $s_B^*(\alpha) > s^*(\alpha)$ and compete, the expected surplus with sharing at stage 0 is:

$$\mathbb{E}[CS(s_B^*(\alpha))] := (1-\alpha)CS^C(s_B^*(\alpha), \overline{\theta}) + \alpha CS^C(s_B^*(\alpha), \underline{\theta}).$$

Hence, regulation increases surplus if the following difference is positive:

$$\begin{aligned}\mathbb{E}[CS(s_B^*(\alpha))] - \mathbb{E}[CS^{no}] &= (1-\alpha)(CS^C(s_B^*(\alpha), \overline{\theta}) - CS^A(\overline{\theta})) \\ &+ \alpha(CS^C(s_B^*(\alpha), \underline{\theta}) - CS^C(s^*(\alpha), \underline{\theta})) > 0.\end{aligned}$$

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When firms share more data under regulation, $s_B^*(\alpha)$ is greater than $s^*(\alpha)$ and the difference $CS^C(s_B^*(\alpha), \underline{\theta}) - CS^C(s^*(\alpha), \underline{\theta})$ is positive. Moreover, $CS^C(s_B^*(\alpha), \overline{\theta})$ is greater than $CS^A(\overline{\theta})$ since the regulator blocks the merger. Overall, in this case, the presence of the regulator increases consumer surplus when it blocks the merger.

When firms share less data in the presence of the regulator, $s_B^*(\alpha)$ is smaller than $s^*(\alpha)$ and the difference $CS^C(s_B^*(\alpha), \underline{\theta}) - CS^C(s^*(\alpha), \underline{\theta})$ is negative. On the other hand, $CS^C(s_B^*(\alpha), \overline{\theta})$ is still greater than $CS^A(\overline{\theta})$. The resulting impact of regulation on consumer surplus is ambiguous.

We can anticipate whether firms share more or less data when they anticipate that the merger will be blocked by the regulator by considering the general class of joint profit functions that are quasi-convex in s, as in the two micro-foundations analyzed in the Appendix. This class of profit functions also includes any monotonous profits, increasing or decreasing in s.

We show that $s_B > s^*(\alpha)$, such that firms share more data if the M&A is blocked. A necessary condition for sharing and competing to be an equilibrium strategy is that $\pi^C(s, \overline{\theta}) > \pi^0$ for at least some values of s. Otherwise, $\Pi_B(s, \alpha) < \pi^0$.

This implies that $\pi^C(s_B^*(\alpha), \overline{\theta})$ increases as we have assumed it is quasi-convex. This means that sharing and competing can be the best strategy for the firm when $\alpha \in (\alpha^B, \alpha_2)$ and $\hat{s}^A < \hat{s}^A(\alpha)$ and the profits with sharing and high synergies are high enough. In this case, firms expect an increase in profits from the synergies when synergies are high.

We can show that $s_B^*(\alpha) > s^*(\alpha)$ using simple first-order conditions on Π_B: either Π_B is increasing at $s^*(\alpha)$, such that $s_B^*(\alpha)$ is greater than $s^*(\alpha)$; or Π_B is decreasing at $s^*(\alpha)$, which also implies that $s_B^*(\alpha)$ is greater than $s^*(\alpha)$ since it means that $\pi^C(s^*(\alpha), \overline{\theta})$ has a downward slope, and we have shown that $s_B^*(\alpha)$ is necessarily on the upward slope of $\pi^C(s, \overline{\theta})$. Overall, firms share more data since doing so increases the competitive profits when synergies are high and the merger is blocked.

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