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Big tech acquisitions ☆

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ABSTRACT

I develop and calibrate a game of startup innovation, incumbent acquisition and merger review, with a focus on industries with uncertainty about the nature of the entrant (complementor or substitute with respect to the incumbent). I estimate that moving from balance of probabilities (the current US and EU system) to balance of harms (proposed for, though not adopted, in the UK) leads to a 15% welfare increase. A complete ban on mergers, in turn, would imply a 35% welfare decrease. No enforcement at all is not significantly different from balance of probabilities. Finally, committing to a more lenient standard than balance of harms increases welfare: under balance of harms, about 25% of all mergers would be blocked, whereas the optimal threshold would lead to only 15% of all mergers being blocked, which in turn would imply an additional 2% increase in welfare. The ordering of proposals is fairly robust to changes in key parameters. I consider some extensions of the basic framework, including reverting the burden of proof of pro-competitive effects.

1. Introduction

Large tech companies, such as Alphabet, Amazon, Apple and Meta, have been the source of intense debate in academic, policy and political circles. This is not without reason: never in history have large corporations like the American giants been so much part of our daily lives and concerns, from privacy to security to quality of service to concentration of political power to freedom of speech. As Scott-Morton et al. (2019) put it, “Google and Facebook have the power of ExxonMobil, the New York Times, JPMorgan Chase, the NRA, and Boeing combined.”

What is the source of big tech power? Many, including the US House of Representatives, believe that acquisitions have played an important role, both acquisitions that add value and acquisitions that preempt competition:

> Several of the platforms built entire lines of business through acquisitions, while others used acquisitions at key moments to neutralize competitive threats (US House of Representatives, 2020).

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And while the dominant platforms collectively acquired several hundred startups from 2000-2020, antitrust agencies did not block a single one of these transactions until, recently, the UK regulator blocked Meta's acquisition of Giphy. This concern for excessive power has led to a push for tougher regulation, in particular a tighter merger policy in the digital space.

In this paper, I evaluate the merits of various merger review proposals. I consider a model with three main players: a startup, an incumbent, and an agency. I assume that the startup may either be a complement or a substitute with respect to the incumbent, and that this uncertainty persists until after a merger takes place. I also assume that payoffs are such that incumbent and startup jointly have an incentive to merge.

The paper's main contribution is to calibrate the theoretical model with parameter values that reflect data from dominant firms and startups in the digital space. The results from the base case suggest that moving from balance of probabilities (the current system in the US and in the EU) to balance of harms (a policy proposed, though not adopted, in the UK) would imply a shift in the percentage of blocked mergers from about zero to about 25% of acquisitions.[1] This in turn would lead to a 15.4% welfare increase. The optimal policy, which accounts for the effect on startup innovative effort, would be to block only 14% of the mergers, which would lead to a 17.6% increase in consumer welfare. In other words, balance of harms performs very close to the optimal policy.

I also show that a total ban on mergers would bias startup research away from complements and in the direction of competition. This is good in of itself, for consumers gain far more from a competitor than from a complement to the incumbent. However, the decrease in startup research would be considerable. Overall, a total ban on mergers would imply a 35% decrease in consumer welfare.

I next perform a series of alternative computations to evaluate the sensitivity of the main results to changes in key parameter values. While the scale of the predicted effects changes, the relative ordering of alternatives is remarkably robust.

I also consider a series of extensions of the basic framework, including the possibility of asymmetric information: with probability λ, the merging parties learn the true nature of the startup (complement or substitute). In this context, reversing the burden of proof that a merger is pro-competitive increases welfare if λ is high (and the firms are able to make the case in Court). However, if λ is small (or the legal barrier is high), then reversing the burden of proof is effectively similar to a ban on mergers, which, as mentioned earlier, implies a drastic decrease in welfare.

■ Related literature. The theoretical foundation of the problem I address is found primarily in Gilbert and Newbery (1982) and in Rasmusen (1988). To the extent that an incumbent monopolist has more to lose from becoming a duopolist than an entrant has to gain from becoming a duopolist, the two parties have an incentive to merge. And the prospect of receiving the acquisition price provides an incentive for an entrant to enter ("entry for buyout").

To the extent that entry requires innovation, "entry for buyout" may be rephrased as "innovation for buyout". This leads to the question of how the prospect of acquisition affects startups' innovation efforts. Although not focused specifically on big tech, Norbäck and Persson (2012) show that "a stricter, but not too strict, merger policy... increases the incentive for innovations for sale." Mason and Weeds (2013), in turn, argue that the prospect of incumbent acquisition may provide the necessary incentive for innovation and derive the optimal merger policy. More recently, Letina et al. (2021) provide "a theory of strategic innovation project choice by incumbents and start-ups which serves as a foundation for the analysis of acquisition policy." They show that "prohibiting acquisitions have a weakly negative innovation effect." However, Katz (2021) shows that a permissive merger policy can discourage entrant innovation.

A series of recent papers address the preemptive nature of startup acquisitions, either through so-called "killer acquisitions" or through the so-called "kill zone." Cunningham et al. (2021) provide compelling evidence of killer acquisitions in the pharmaceutical industry, that is, acquisitions that have a pure pre-emptive motive and are never actually put to use. Kamepalli et al. (2019) argue that "the prospect of an acquisition by the incumbent platform undermines early adoption by customers, reducing prospective payoffs to new entrants" (what they refer to as the "kill zone"). Motta and Shelegia (2021) develop a rather different view of the kill zone. They argue that "the possibility of being acquired by the incumbent tends to push the rival towards developing a substitute rather than a complement. By choosing the former, potential gains from the acquisition are created (in the form of suppression of competition): as long as the rival has some bargaining power in the determination of the takeover price, it will then benefit from entering the 'kill zone'."

Fumagalli et al. (2020) focus on the implications of financing constraints faced by a startup. They consider a model where the incumbent can submit a takeover bid in two moments: either prior to project development, before the start-up asks for funding; or after the start-up secures funding and successfully develops, i.e., when it is committed to enter the market. They show that an optimal merger policy commits to blocking late takeovers, which in turn induces the incumbent to move early on startups that are financially constrained. They also show that "authorization of late takeovers entails a trade-off between the ex-ante relief of financial constraints and the ex-post increase in market power. This is related to some of the trade-offs I will develop in Section 3.

A series of theory papers analyze the implications of the incumbent/startup setting for the *direction* of innovative activity. Cabral (2018) develops a dynamic model of innovation and derives conditions such that the possibility of buyout increases incremental innovation but decreases radical innovation. Denicolo and Polo (2021) develop a dynamic model somewhat related to Cabral (2018). The novelty is that, if the incumbent's dominance depends on its past activity levels, then serial acquisitions lead to entrenchment-of-monopoly effect. Bryan and Hovenkamp (2020a) show that startups are biased toward inventions that help improve the leader's

[1] The estimate of the fraction of blocked mergers assumes that all profitable mergers are attempted. However, anticipating that an acquisition might be blocked, we should expect many profitable mergers not to be reviewed at all. Therefore, the *observed* fraction of blocked mergers would be lower than the numbers shown in the text.

product versus those that help the laggard catch up technologically. Callander and Matouschek (2022) argue that "the prospect of acquisition makes innovation more profitable but simultaneously suppresses the novelty of innovation as the entrant seeks to maximize her value to the incumbent. This reversal suggests a positive role for a strict antitrust policy that spurs entrepreneurial firms to innovate boldly." Similarly, Moraga-González et al. (2021) consider a startup that chooses a portfolio including a "rival" project (which threatens the position of an existing incumbent) and a "non-rival" project. They show that, "anticipating its acquisition by the incumbent, the start-up strategically distorts its portfolio of projects to increase the (expected) acquisition rents. Depending on parameters, such a strategic distortion may result in an alignment or a misalignment of the direction in which innovation goes relative to what is socially optimal. Moreover, prohibiting acquisitions may increase or decrease consumer surplus." Also along similar lines, Gilbert and Katz (2022) "examine the effects of merger and merger policy on a potential entrant's pre-merger product choice" and "establish conditions under which the possibility of merger can induce an entrant to inefficiently imitate an incumbent's product instead of innovating with a more differentiated product."

Closest to the present paper, Wickelgren (2021) present a model of innovation, acquisition and merger review. This model shares several of the features of my model. One important difference is that Wickelgren (2021) considers a potential entrant who decides the nature of its project (complement or substitute). By contrast, I assume that each potential entrant is given an idea by Nature, together with a probability that the idea will be a potential competitor (as opposed to complementor) with respect to the incumbent. Moreover, I develop a calibration strategy that allows me to estimate the sign and order of magnitude of the main results.

Methodologically speaking, all of the above papers follow an applied theory approach and produce possibility results. In fact, this approach characterizes most of the literature on big tech acquisitions. One exception to this characterization is given by Cavenaile et al. (2021), who develop and estimate a general equilibrium model with Schumpeterian innovation, oligopolistic product market competition, and endogenous M&A decisions. Their results suggest that strengthening antitrust enforcement could deliver substantially higher gains. They also emphasize the importance of dynamics, arguing that the dynamic long-run effects of antitrust policy on social welfare are an order of magnitude larger than the static gains from higher allocative efficiency in production. Fons-Rosen et al. (2021) provide an alternative attempt at calibrating a model of innovation and acquisition. They develop an endogenous growth model with heterogeneous firms and acquisitions. They discipline the model by matching aggregate moments and evidence from a rich micro dataset on acquisitions and patenting. Their findings indicate that stricter antitrust policy would trigger somewhat higher growth.[2]

There are also a few empirical retrospective analyzes worth mentioning. Argentesi et al. (2021) present a broad retrospective evaluation of mergers and merger decisions in markets dominated by multisided digital platforms. They then discuss theories of harm that have been used or, alternatively, could have been formulated by authorities in these cases. Jin et al. (2022), in turn, use a unique taxonomy developed by S&P Global Market Intelligence to compare the M&A activities of GAFAM to other top acquirers from 2010 to 2020. Among other results, they find "no evidence suggesting that a GAFAM acquisition in a category, compared to similar categories without GAFAM acquisitions, is correlated with a slowdown in the number of new acquirers acquiring in that category." Gautier and Lamesch (2021) study 175 acquisitions by GAFAM over the period 2015-2017. Their analysis shows that acquisitions mostly strengthen the incumbents' core market segments and rarely allow the incumbent to expand into new areas. Moreover, most of the acquired products are shut down post acquisition, which suggests that GAFAM mainly acquire firm's assets (functionality, technology, talent or IP) to integrate them in their ecosystem rather than the products and users themselves. Although these papers talk about theory, their main purpose is to analyze historical data. I will return to these studies in Section 4, when I calibrate the theoretical model developed in Section 2.

Finally, there are also a number of more policy-oriented papers that address the issue of merger policy in the context of big tech, including Cabral (2021), who discusses policy implications of Cabral (2018), and Motta and Peitz (2021), who offer some policy recommendations on how to deal with mergers in digital industries.[3]

2. Model

In order to better understand the interplay between merger policy and innovation incentives, I consider a model (game) with three main players: a startup, an incumbent, and an agency. As anecdotal and empirical evidence suggests, being acquired by a large incumbent is an important option (though not the only one) for a startup; and acquiring startups is an important part of the business model of large incumbents. Finally, regulatory agencies play an important role (or should play an important role) by allowing or blocking such acquisitions. The main goal of the paper is to understand the interplay between these three stages of the process, including the "feedback" effect that merger policy might have on the incentives for startups to innovate.

As Scott-Morton et al. (2019) aptly put it, "digital markets typically have high levels of uncertainty and move quickly." I capture this uncertainty in the innovation process by assuming that, in addition to the possibility of failure (no innovation at all), a successful startup may either be a substitute (s, probability α) or a complement (c, probability $1-\alpha$) with respect to the incumbent. I assume the startup knows the value of α (which is exogenously assigned by Nature) but not the precise nature of the innovation (s or c). This is consistent with Crémer et al.'s (2019) observation that it "is frequently difficult to distinguish pro-competitive or neutral deals from anti-competitive deals."[4] Specifically, the timing of the game is as follows:

[2] Relatedly, Shapiro (2009) proposes (in an appendix) a calibration exercise to better understand the role of potential competition in the context of the *Microsoft* case.

[3] Calvano and Polo (2021) offer a survey of innovation issues in digital markets.

[4] It is difficult even for the merging parties themselves, I would add — though in Section 5 I will consider the possibility of asymmetric information.

Table 1
Payoffs for incumbent, entrant and agency as a function of innovation type and outcome.

	no acquisition	acquisition
complement	(π_m, θ_m, μ_m)	$(\pi_c - p, p, \mu_c)$
substitute	(π_s, θ_s, μ_s)	$(\pi_m - p, p, \mu_m)$

1. Nature generates value of α, the likelihood that the startup is type s, from the cumulative distribution function $F(\alpha)$. The realization of α common knowledge.
2. The startup invests $\gamma\, x^\sigma$ in order to innovate with probability x.
3. If the startup is not successful, then the game ends. If the startup is successful, then the incumbent negotiates its acquisition. This takes place according to a generalized Nash bargaining process (the incumbent's bargaining power is given by β). The resulting acquisition price is given by p.
4. The agency determines if the acquisition is allowed to go through based on the value of α.[5] (Different merger-review regimes correspond to different rules, in particular different α-threshold rules.)
5. Nature decides if the startup is type s or type c.
6. Payoffs are received by the incumbent, the startup, and the agency.

I next elaborate on each of these stages. First, I note that, while I assume the startup only chooses the value x, the model can be seen as a predictor of the *direction* of innovative activity as well. The way to think about it is that Nature offers a series of potential "ideas", each corresponding to a value of α. To the extent that x depends on the value of α (it does), the startups' choices effectively determine the direction of innovative activity of the "system" as a whole.[6]

I assume the acquisition negotiation stage has the structure of Nash bargaining and results in a conditional acquisition price p. By "conditional" I mean that the acquisition (and the p transfer) only takes place if the merger is allowed to take place. Moreover, following common practice in applied work, I consider a generalized Nash solution whereby the incumbent has a weight $\beta \in (0,1)$ (and the startup a weight $1-\beta$). This assumption reflects the evidence from the digital space of great asymmetry in bargaining power between incumbent and startup.[7]

An important feature of the model is its information structure, which reflects two important features of the digital space. First, there is great uncertainty regarding business models, which I model by assuming that the target can be of two different types (s with probability α, c with probability $1-\alpha$). Second, this uncertainty is resolved gradually, and various decisions are made at intermediate levels of uncertainty. I model this by assuming that, at the time when innovation and acquisition decisions are made, all that is known is the likelihood α that the target is of type s.[8]

The above extensive form describes a sequence of moves but not calendar time. I effectively assume that the time lag between merger review and the eventual resolution of uncertainty is sufficiently long that it is not practical for the agency to simply wait before making a decision.

Table 1 displays payoffs as a function of startup type (s or c) and the acquisition outcome (no acquisition or acquisition). Each cell includes the incumbent's payoff, the startup's payoff, and the agency's payoff. Although the focus of the paper is not on the goals of antitrust, I will assume (namely in the calibration in Section 4) that the agency's payoff coincides with consumer surplus, which I will simply refer to as welfare.

The subscript s in the payoff terms stands for duopoly competition between the incumbent and an s-type startup (who is a substitute and possibly a replacement for the incumbent). The subscript c stands for the state when a c-type startup is absorbed by the incumbent, thus creating value both for the incumbent and for consumers. Finally, the subscript m corresponds to the cases when the incumbent remains a monopolist. This may happen in two different ways: First, a potential complement that is not acquired (and does not affect the incumbent's payoff).[9] Second, a potential competitor that is acquired: a so-called killer acquisition. A third possibility, which I don't need to model explicitly, is that innovation fails to take place.

I make the following assumption regarding payoff values:

[5] In the basic version of the model there is no asymmetric information between firms and the agency. As such, the transactions price provides no additional information with respect to α, which is common knowledge. I will later consider the possibility of asymmetric information.

[6] In the previous sentence, I use the plural "startups": while the model is focused on a focal startup, the applied portion of the paper integrates over the distribution of α, which is best thought of as the universe of startups. In fact, in Section 4, I will discuss how different merger policy proposals affect the *direction* of innovative activity, that is, the average α of successful startups.

[7] A more complete model would consider explicitly the source of the asymmetry, for example, the existence of multiple startups with similar features competing to be acquired, or multiple incumbents seeking a given target.

[8] In Section 5, I consider a third information feature, namely the possibility that along the way the incumbent acquire better information than the agency. I model this by assuming that, with probability λ, the incumbent knows the target's type before the agency, in particular, before the agency makes a decision on the merger.

[9] I make the assumption that when a potential complement to the incumbent is not acquired, such potential complement has no effect on the incumbent's payoff. In other words, the latter remains the same as it was before the potential complement successfully innovated. This is probably a good first-order approximation to real-world payoffs. An extension of the model would consider the distinction between the two different states. It would not affect the qualitative nature of the analytical results and have a marginal effect on the calibration exercise presented in the next section.

Assumption 1. $\pi_c > \pi_m > \pi_s \geq 0$; $\mu_s > \mu_c > \mu_m > 0$

Basically, this implies that the incumbent is best off when acquiring a complement and worse off when competing against a substitute. I note that the inequality $\pi_s \geq 0$ is weak, as I will allow for the possibility that the incumbent is replaced by the startup. The agency's order of preferences differs from the incumbent's: The agency is best off when there is competition or disruptive innovation (whereby the startup replaces the incumbent); and worse off when the status quo is maintained.

Although for much of the paper I will treat the above payoffs as given values, they are best thought of as expected values from given probability distributions. For example,

$$\mu_s = \int \mu_s^{\circ}(\psi)\, f(\psi)\, d\,\psi$$

where ψ measures the competitive threat posed by an s-type startup and $f(\psi)$ is its density distribution of ψ. This is particularly important if one wants to model the possibility of disruptive innovation, that is, the case when an s startup replaces the incumbent. While this may be a small probability event, its effect in terms of welfare can be very high. Assuming a distribution of ψ also allows for a more realistic calibration, given the wide variety in size of big tech acquisition targets.

I make a second assumption regarding parameter values:

Assumption 2. $\alpha\,\theta_s + (1-\alpha)\,\theta_m < \alpha\,(\pi_m - \pi_s) + (1-\alpha)\,(\pi_c - \pi_m)$

This assumption implies that there is room for a mutually profitable acquisition. Specifically, the left-hand side of Assumption 2 is the startup's expected value from going solo. Basically, this is given by the probability that the startup is a competitor times the payoff from competing against the incumbent plus the probability that the startup is a complementor times the payoff of being a solo complementor. The right-hand side is the incumbent's expected gain from acquisition: With probability α, the startup is a substitute, in which case the acquisition has a pre-emption value of $\pi_m - \pi_s$. With probability $1-\alpha$, the startup is a complementor, in which case the acquisition creates value $\pi_c - \pi_m$.

Essentially, Assumption 2 corresponds to the assumption in Gilbert and Newbery (1982) that the incumbent has more to lose from facing competition than the entrant has to gain from becoming a competitor. Note that this is consistent with the possibility that the startup's value of ψ is so high that it replaces the incumbent if not acquired. However, I assume that there is uncertainty regarding the value of ψ (or α, for that matter) at the moment of acquisition, and that the Gilbet-Newbery condition (Assumption 2) applies in terms of *expected* values at the time of acquisition. Were this assumption not to hold, then even absent a regulatory agency an acquisition would not take place.

Stage 4 in the above extensive form is discussed in a rather laconic way. The main goal of the paper is to evaluate alternative systems of merger review, including both the present ones and the various proposals on the table. A first reference point is what we might refer to as ***no enforcement***: no acquisition is ever blocked by the merger authority. Some might consider this a good approximation to the de facto approach followed in the US with respect to big tech acquisitions. A second possibility is what I will refer to as ***balance of probabilities***, a system that I believe is close to the current EC regime.[10] The idea is that a merger is blocked if and only if it is more likely to have an anti-competitive effect than a pro-competitive effect. This is contrasted with the system proposed by a variety of economists (including the authors of the Furman report), namely the concept of ***balance of harms***. This differs from balance of probabilities in that the probability of a pro-competitive or anti-competitive effect is weighted by its consumer surplus effect. I also consider the possibility of a ***total ban*** on mergers, the opposite extreme of no enforcement.[11]

All of the four merger policies listed above have one thing in common: they are all based on a threshold $\hat{\alpha}$ of a startup's promise to compete against the incumbent. In this context, it makes sense to consider a fifth threshold policy, namely the value of $\hat{\alpha}$ that maximizes welfare. I denote this as the ***optimal policy***, noting however that it's optimal within a particular class of α-threshold policies. In sum, I model the various proposals as follows:

- ***no enforcement***: $\hat{\alpha} = \alpha_l = 1$ (l for laissez-faire)
- ***complete ban***: $\hat{\alpha} = \alpha_b = 0$ (b for ban)
- ***balance of probabilities***: $\hat{\alpha} = \alpha_p = .5$ (p for probabilities)
- ***balance of harms***: $\hat{\alpha} = \alpha_h$, where α_h (h for harm) solves

$$\alpha\,\mu_s + (1-\alpha)\,\mu_m = \alpha\,\mu_m + (1-\alpha)\,\mu_c$$

- ***optimal policy***: $\hat{\alpha} = \alpha_o$, the value of α_o (o for optimal) that maximizes ex-ante welfare

[10] Federico et al. (2020) state that the "criterion generally applied by antitrust enforcers around the world, including in the United States and the EU, [is that] a merger is considered anticompetitive if it may substantially lessen competition." As I will argue later, in the EU this is made specific by a balanced-of-probabilities test.

[11] In Section 5, I consider one additional possible feature of a merger review scheme, namely the reversal of the burden of proof.

Table 2
Main notation used in the paper.

Variable	Description
Outcomes	
m	startup is a complement and remains independent
c	startup is a complement and is acquired
s	startup is a substitute and is not acquired
α	probability that startup is a substitute to incumbent
f(ξ)	distribution of startup's value conditional on being type c (Section 4)
f(ψ)	distribution of startup's value conditional on being type s (Section 4)
λ	probability that merging parties learn true nature of startup (Section 5)
Payoffs	
θ_z	startup's payoff in state $z \in \{c, s, m\}$
π_z	incumbent's payoff in state $z \in \{c, s, m\}$
μ_z	agency's payoff in state $z \in \{c, s, m\}$
Decisions and equilibrium values	
x	startup's research effort
y	incumbent's research effort (Section 5)
p	startup acquisition price
Merger policy regimes	
0	all acquisitions allowed
1	all acquisitions blocked
p	balance of probabilities
h	balance of harms
o	optimal threshold
A_z	agency welfare under regime $z \in \{l, b, p, h, r\}$
Other	
β	incumbent's acquisition bargaining weight
γ,σ	parameters of innovation cost function

In the next section, I derive some theoretical results comparing these policies. In Section 4, I calibrate the model to replicate various moments of the AAAM ecosystem so as to be more precise about the "horse race" between the above merger policies. To conclude this section, and considering the abundance of notation used in the paper, Table 2 summarizes the main variables considered.

3. Comparing proposals

In this section, I solve the model presented in the previous section, considering the various alternative versions of Stage 4, that is, various $\widehat{\alpha}$ values of a threshold-type merger policy.

■ **No enforcement of mergers.** Suppose that no merger is ever blocked. Consider the acquisition stage. Following the assumption of Nash bargaining, where the incumbent's bargaining power is indexed by β, the acquisition price is given by

$$\max_{p} \; \Big(\alpha\,\pi_m + (1-\alpha)\,\pi_c - p - \big(\alpha\,\pi_s + (1-\alpha)\,\pi_m\big)\Big)^{\beta} \; \Big(p - \big(\alpha\,\theta_s + (1-\alpha)\,\theta_m\big)\Big)^{1-\beta} \tag{1}$$

Consider the expression in brackets raised to β. The first part, $\alpha\,\pi_m + (1-\alpha)\,\pi_c - p$ is the incumbent's payoff if an acquisition takes place: With probability α, the target is a substitute, in which case the acquisition kills a potential competitor and maintains profits at the π_m level. With probability $1-\alpha$, the target is a complement, in which case the acquisition increases incumbent's profits from π_m to $\pi_c > \pi_m$. To the value of expected profits, we must subtract the acquisition price p. If no acquisition takes place, then the incumbent's profit is given by $\alpha\,\pi_s + (1-\alpha)\,\pi_m$: With probability α, the incumbent must compete against a substitute startup and profits drop to π_s. With probability $1-\alpha$, the startup is a potential complement but remains an independent entity, so that incumbent profits remain at π_m.

To put it differently, the expression in brackets raised to β may be re-written as $\alpha\,(\pi_m - \pi_s) + (1-\alpha)\,(\pi_c - \pi_m) - p$. This means that acquiring the startup is beneficial for one of two reasons: If the startup is type s (probability α), then the killer acquisition saves the incumbent a loss in profit of $\pi_m - \pi_s$. If, by contrast, the startup is type c (probability $1-\alpha$), then acquisition leads to an increase in profits to the tune of $\pi_c - \pi_m$.

Finally, the expression in brackets raised to $1-\beta$ measures the startup's expected gain from an agreement: If an acquisition takes place, then the startup's payoff is simply the sale price p. By contrast, if no acquisition takes place, then either the startup is type s, in which case it earns duopoly profits θ_s; or the startup is type c, in which case it remains as an independent entity as earns θ_m.

The maximization problem (1) implies

$$p = (1-\beta)\;\Big(\alpha\,(\pi_m - \pi_s) + (1-\alpha)\,(\pi_c - \pi_m)\Big) + \beta\,\Big(\alpha\,\theta_s + (1-\alpha)\,\theta_m\Big) \tag{2}$$

We can now look at the startup's innovation problem. Anticipating that a merger will not be blocked, the startup chooses x so as to solve

$$\max_x \; x\,p - \gamma\,x^\sigma$$

which leads to

$$x_0 = \left(\frac{p}{\gamma\sigma}\right)^{\frac{1}{\sigma-1}} \tag{3}$$

where we assume $\sigma > 1$ and the 0 subscript stands for the case when no merger is blocked. Finally, the agency's welfare is given by

$$\begin{aligned} A_0 &= (1-x_0)\,\mu_m + x_0\,(\alpha\,\mu_m + (1-\alpha)\,\mu_c) \\ &= \mu_m + x_0\,(1-\alpha)\,(\mu_c - \mu_m) \end{aligned} \tag{4}$$

Intuitively, the agency's payoff starts at the baseline μ_m (the current level of consumer surplus). If the startup's innovation effort is successful, and given that the startup is acquired by the incumbent, then: With probability α, we have a killer acquisition and consumer surplus remains the same as before. With probability $1-\alpha$, the incumbent acquires a complementor, which leads to a welfare increase of $\mu_c - \mu_m$.

■ Complete ban on mergers. Consider now the opposite extreme, that is, the case when all mergers are blocked. Anticipating that no acquisition ever takes place, the startup picks x so as to solve

$$\max_x \; x\,\left(\alpha\,\theta_s + (1-\alpha)\,\theta_m\right) - \gamma\,x^\sigma \tag{5}$$

which leads to

$$x_1 = \left(\frac{\alpha\,\theta_s + (1-\alpha)\,\theta_m}{\gamma\,\sigma}\right)^{\frac{1}{\sigma-1}} \tag{6}$$

where the 1 subscript stands for the case when all mergers are blocked. Finally, the agency's payoff is given by

$$\begin{aligned} A_1 &= (1-x_1)\,\mu_m + x_1\,\left(\alpha\,\mu_s + (1-\alpha)\,\mu_m\right) \\ &= \mu_m + x_1\,\alpha\,(\mu_s - \mu_m) \end{aligned} \tag{7}$$

As in (4), the agency's payoff starts at the baseline μ_m (the current level of consumer surplus). If innovation is successful (probability x_1) and considering that there is no acquisition, then: With probability $1-\alpha$, we have a complementor which, absent acquisition by the incumbent, adds no value to consumers. With probability α, we have a substitute competing with the incumbent, which leads to a welfare increase of $\mu_s - \mu_m$.

■ Balance of probabilities. According to the Court of Justice of the European Union:

> The Commission is, in principle, required to adopt a position, either in the sense of approving or of prohibiting the concentration, in accordance with its assessment of the economic outcome attributable to the concentration which is most likely to ensue.

Streel (2020) argues that "this standard of proof relates to the most probable post-merger market evolution." In terms of the present framework, this would seem to imply that a merger is approved if and only if $\alpha < 50\%$. It follows that

$$A_p = \mu_m + \int_0^{.5} x_0\,(1-\alpha)\,(\mu_c - \mu_m)\,d\,F(\alpha) + \int_{.5}^{1} x_1\,\alpha\,(\mu_s - \mu_m)\,d\,F(\alpha) \tag{8}$$

where the subscript p stands for balance of probabilities.

This balance of probabilities regime has been criticized on the grounds that it is not sufficient to compare the likelihood of two different scenarios: one must also weigh the costs and benefits of each of these scenarios. In particular, it has been argued that the foregone benefits from competition and/or disruptive innovation can be considerably higher than the benefits from the acquisition of a complementor, so that the threshold $\alpha = .5$ is not appropriate. This naturally leads to the next proposal, balance of harms.

■ Balance of harms. As Furman et al. (2019) rightly put it, a system of balance of probabilities "is unduly cautious." Instead, they recommend that

> Assessment should be able to test whether a merger is expected to be on balance beneficial or harmful, taking into account the scale of impacts as well as their likelihood (Furman et al., 2019).

This they refer to as a "balance of harms" approach. In terms of my model, a "balance of harms" approach corresponds to blocking a merger if and only if

$$\alpha\,\mu_s + (1-\alpha)\,\mu_m > \alpha\,\mu_m + (1-\alpha)\,\mu_c \tag{9}$$

This can be re-written as

$$\alpha\,(\mu_s - \mu_m) > (1-\alpha)\,(\mu_c - \mu_m)$$

This illustrates the concept of balance of harms: It is not sufficient to compare the probabilities of each outcome (α vs $1-\alpha$), one must also factor in the benefit (or harm) following these probabilities. With probability α, the target is of type s. This implies that blocking the merger generates a benefit $\mu_s - \mu_m$ from competition (or disruptive innovation). With probability $1-\alpha$, the target is of type c. This implies that allowing the merger generates a benefit $\mu_c - \mu_m$ from the integration of a complementor with the incumbent. It may well be the case that $\alpha < 1-\alpha$ (anti-competitive outcome is less likely) but $\mu_s - \mu_m$ is so much greater than $\mu_c - \mu_m$ that blocking the merger leads to a higher expected benefit.

Specifically, the agency is better off blocking a merger when the expected foregone benefit implied by a killer acquisition, $\alpha\,(\mu_s - \mu_m)$, outweighs the likely benefit from a synergetic acquisition, $(1-\alpha)\,(\mu_c - \mu_m)$. If α is very large, then the likelihood of a killer acquisition is sufficiently high to make it worthwhile to block the merger. In fact, (9) may be re-written as

$$\alpha > \alpha_h \equiv \frac{\mu_c - \mu_m}{(\mu_c - \mu_m) + (\mu_s - \mu_m)} \tag{10}$$

It follows that the agency's payoff is given by

$$A_h = \mu_m + \int_0^{\alpha_h} x_0\,(1-\alpha)\,(\mu_c - \mu_m)\,dF(\alpha) + \int_{\alpha_h}^{1} x_1\,\alpha\,(\mu_s - \mu_m)\,dF(\alpha) \tag{11}$$

where the subscript h stands for balance of harms.

How does balance of harms compare to balance of probabilities? As mentioned earlier, the criticism of balance of probabilities is that it is "unduly cautious" in blocking a merger insofar at it does not properly weigh costs and benefits. The problem is that, according to the majority of experts, rare as a type s startup may be, the benefits brought about by competition are considerably higher than the benefits brought about by the acquisition of a complementor.[12] Formally, the above reasoning corresponds to the following result, the proof of which follows directly from (10):

Proposition 1. *$\alpha_h < \alpha_p$ if and only if $\mu_s - \mu_m > \mu_c - \mu_m$*

In other words, balance of probabilities is too lenient on mergers compared to balance of harms. I will next show that balance of harms is too tough on mergers compared with the optimal threshold that takes the endogeneity of x into account.

■ **Optimal threshold.** Equations (3)–(7) characterize the trade-offs faced by the agency. For a given value of x (the startup success probability), welfare from blocking a merger, given by (7), is greater than welfare from allowing a merger, given by (4), if and only if $\alpha\,(\mu_s - \mu_m) > (1-\alpha)\,(\mu_c - \mu_m)$. However, the value of x is not invariant with respect to merger policy. In fact, Assumption 2 implies that x_0, the startup investment anticipating a merger will not be blocked, is greater than x_1, the startup investment anticipating a merger will be blocked. This has several implications. First, the expected value of x, given by

$$\mathbb{E}(x) = \int_0^{\widehat{\alpha}} x_0\,dF(\alpha) + \int_{\widehat{\alpha}}^{1} x_1\,dF(\alpha) \tag{12}$$

is strictly increasing in α. Second, and more important, the α_h threshold, which is ex-post optimal, is too low from an ex-ante point of view:

Proposition 2. *$\alpha_h < \alpha_o$*

In words, balance of harms is too harsh on mergers compared to a policy that takes into account the effect of blocking mergers on innovative effort. The proof of Proposition 2, which may be found in the Appendix, is based on the envelope theorem. At $\widehat{\alpha} = \alpha_h$, the derivative of ex-post welfare with respect to $\widehat{\alpha}$ is zero, since $\widehat{\alpha} = \alpha_h$ maximizes ex-post welfare. However, the effect of an increase in $\widehat{\alpha}$ on x is strictly positive, as we saw before.

Similar results to Proposition 2 may be found in Mason and Weeds (2013), Jaunaux et al. (2017), and Gilbert and Katz (2022).[13] Proposition 2 is reminiscent of a similar result on patents and innovation incentives dating back at least to Tandon (1982) (see also Gilbert and Shapiro, 1990; and Klemperer, 1990). Forcing a patent holder to license their innovation so that equilibrium price is marginally lowered from monopoly price has a second-order effect on innovation incentives but a first-order effect on consumer welfare. In this sense, we may think of Proposition 2 as the "dual" of the result on the level of patent protection. The comparative statics of the result on IP protection is that a marginal weakening of patent protection has a positive first-order effect on welfare and

[12] See, for example, Scott-Morton et al. (2019), Furman et al. (2019), Crémer et al. (2019).

[13] But see Søgard (2009) for the opposite case.

a second-order effect on incentives. The comparative statics of Proposition 2 is that a marginal weakening of merger policy has a second-order effect on ex-post welfare but a first-order positive effect on innovation incentives.

To summarize the present section, we considered various merger policies based on a blocking threshold $\hat{\alpha}$. Our theoretical analysis establishes a general ordering of the various policies:

$$0 = \alpha_b < \alpha_h < \alpha_o \quad \text{and} \quad \alpha_h < \alpha_p < \alpha_l = 1$$

So far, we have considered consumer surplus (or simply welfare) as the relevant performance measure. However, there are other potentially relevant performance measures. The next set of results pertains to these alternative performance measures as a function of $\hat{\alpha}$. First, one may be concerned with the level of innovation, as measured by the number of successful startups, as a function of the level of $\hat{\alpha}$.

Proposition 3. *In equilibrium, the number of successful startups is increasing in $\hat{\alpha}$.*

The intuition is simple: one of the sources of innovation incentives is the prospect of being acquired. For a given α, the equilibrium value of x is greater if α is lower than $\hat{\alpha}$. A more stringent merger policy thus implies weakly lower innovation effort, strictly lower for some values of α.

The main countervailing effect of an increase in α is that the probability of a killer acquisition is greater, which in turn leads to less competition:

Proposition 4. *The expected number of competitors (successful s-type startups who are not acquired) is decreasing in $\hat{\alpha}$*

The intuition is that an increase in $\hat{\alpha}$ implies that all successful entrants within the interval between old and new threshold are acquired, thus decreasing the number of competitors from a positive value to zero.

Finally, a less intuitive result refers to the *direction* of innovative activity. While I assume the startup only chooses the value x, the model can be seen as a predictor of the direction of innovative activity as well. The way to think about it is that Nature offers a series of potential "ideas", each corresponding to a value of α. To the extent that x depends on the value of α (it does), the startup's choices effectively determine the direction of innovative activity of the "system" as a whole. As mentioned in the literature review, prior research (e.g., Callander and Matouschek, 2022) suggests that a tougher merger policy (a lower $\hat{\alpha}$ in the present context) might be the solution to counteract the pro-incumbent bias we find in the many so-called digital innovation eco-systems. However, as the next result shows, this is not necessarily so:

Proposition 5. *In equilibrium, the expected valeu of α of successful startups is if decreasing (resp. increasing) if α is sufficiently low (resp. high).*

Suppose we start from a laissez-faire merger policy: $\hat{\alpha} = 1$. A decrease in $\hat{\alpha}$ to $\hat{\alpha}' < 1$ implies that, when $\hat{\alpha}' < \alpha < 1$, innovation effort is now lower. Since this is the only instance when the value of x varies, and since the average α of successful ventures is strictly between 0 and 1, it follows that there is a decline in the average valeu of α of successful startups.

This section presented a series of analytical results. However, a number of questions persist: How large are the differences between the thresholds corresponding to the various policies? How much do they matter from a welfare point of view? What is the relation between α_o and α_p, the one relation we are unable to establish at the level of generality considered so far? In the next section, I attempt to calibrate the model based on a variety of data and moments from Alphabet, Amazon, Apple and Meta (AAAM).

4. Calibration

In the previous section, I derived a series of analytical results regarding different alternative merger policies. In this section, I attempt to go a bit further and provide a quantitative estimate of the performance of different alternative merger policies. Specifically, I calibrate the model developed in the previous section to be broadly consistent with one of the AAAM firms. As a starting point, I assume market valuation provides a good estimate of the incumbent's discounted annual profits. Specifically, I assume $\pi_m = \$200$ bn, where profit values are measured as the present value of future profit streams. The value $\pi_m = \$200$ bn is approximately the average value of an AAAM firm during 2000-2020. I should note that the value of π_m serves exclusively as a scaling factor. As such, it does not have an influence on the ordering of alternatives.

Next, I focus on the value added to the incumbent by acquiring a c target, which I denote by ξ and measure as a percentage of the incumbent's value. Assuming that all acquisitions were of type c, and assuming that all growth in value by AAAM resulted from acquisitions, then the average increase in incumbent value on a per-acquisition basis would be given by

$$\xi = \sqrt[n]{\frac{V_1}{V_0}}$$

where V_1 is final value, V_0 initial value, and n the number of acquisitions. Proceeding in this manner, I obtain an average value of 2.5% per acquisition.[14] Assuming that 20% of the increase in incumbent value during 2010–2020 was due to acquisitions, I finally assume a base value of $\xi = .5\%$. Some might consider 20% of incumbent's growth due to acquisition to be too high, considering the incumbents' enormous research budgets compared to the startup's. However, an apples-to-apples comparison should consider the *overall* investment by non-incumbents, not just that of the successful startups. Moreover, there are also reasons to believe $\xi = .5\%$ may underestimate the value created by a c acquisition.[15] All in all, I believe $\xi = .5\%$ to be a reasonable estimate. Given the importance of this parameter, I consider an alternative lower value1 of 0.1% and an alternative higher value of 1%.

I assume the average price of an acquisition is \$490 m. I obtain this value as follows. I collect all of the AAAM's acquisitions for which a price is listed on Wikipedia. I then divide the acquisition price by the incumbent's market cap at the time of the acquisition. Then I take the average of these values and multiply it by \$200 bn, my assumption of market cap in the simulation. This average price is lower than the average value reported in Jin et al. (2022), \$1.4bn. However, it should be noted that the market cap of AAAM firms has increased enormously in recent years, so that acquisition prices as a fraction of market cap are considerably lower. Finally, I note that I will allow for variability in acquisition price.

Regarding the probability that a startup is a substitute (i.e., a competitor), I assume that it is exponentially distributed with mean $\overline{\alpha} = 5\%$ and truncated at 1, so that $\alpha \in [0, 1]$.[16] If we assume that the historical acquisitions are a representative sample of the F distributions, this amounts to assuming that 5% of the acquisitions were killer acquisitions. This is consistent with the idea that the "the majority of acquisitions by large digital companies are likely to be either benign or beneficial for consumers, though a minority may not be" (Furman et al., 2019). In an early version of Gautier and Lamesch (2021), the authors state that "from our check for possible 'killer acquisitions', it appears that just a single one in our sample could potentially be qualified as such." This would correspond to $\overline{\alpha} = 1/175 \approx 0.6\%$. Cunningham et al. (2021) estimate ("conservatively") that 5.3% to 7.4% of acquisitions in their sample are in the "killer" category. However, their analysis is focused on the pharmaceutical industry, not the digital space. One should also add that, to the extent that the current system is not characterized by absence of enforcement but rather by balance of probabilities, and assuming that players anticipate this regime, then we should not observe any attempt of acquisitions of targets with $\alpha > .5$, in which case the 0.6% found in the above-mentioned empirical study under-estimates the actual value of α. Given the importance of this parameter, I will also consider the alternative values 1% and 10%.

My next set of empirical assumptions refers to the number of potential startups and the number of successful ones. This is extremely hard to pin down. Fortunately, I find that it does not have a major effect on the ordering of alternative policies. Basically, I cannot separately identify the number of potential startups and the probability of success: there are multiple combinations leading to the same observed number of successful startups. But fortunately, it's the number of successful startups — that is, targets for incumbent acquisition — that matters, and these I can observe from the data. That said, the model calls for the calibration of the number of potential startups. There are hundreds of thousands of startups throughout the world, but clearly not all are equally positioned to be acquired by one of the tech giants. In my base case, I assume that there are 10,000 startups, whereas the number of acquisitions (by one incumbent) is 10 per year. The first number is broadly in line with the number of applicants to YCombinator (see ycombinator.com), the world's leading startup accelerator. The number of acquisitions, in turn, is broadly in line with the historical data on acquisitions, which imply an annual average of 9.5 acquisitions per year per incumbent.

The parameter β measures the incumbent's bargaining power in the generalized Nash solution concept. As mentioned earlier, it would be more rigorous to explicitly consider the differences in outside options that lead the incumbent to effectively enjoy greater bargaining power. I follow the practice, typical in applied research, of using the generalized Nash solution. I assume a base value of .8. Some might argue that the asymmetry between AAAM firms and startups is greater than this value, in fact closer to $\beta = 1$, the value implied by the assumption that the incumbent makes a take-or-leave-it offer to the startup. However, the evidence suggests that there is considerable asymmetric information, which in turn suggests a value lower than 1 (where $1 - \beta$ measures the startup's information rent when the incumbent makes a take-it-or-leave-it offer). I consider alternative values $\beta = .7$ and $\beta = .9$.

Last but not least, one needs to take a stance on the elasticity of innovation with respect to the prize from innovation, ϵ_{xp}. This parameter is very much at the core of the paper. Consider the case (arguably the present situation) when no merger is challenged, so that the prize from innovation is given by the acquisition price p. Scherer (1982) reports estimates of ϵ_{xp} in the $[.443, .904]$ range. In the base case, I assume that $\epsilon_{xp} = .6$. I also consider a lower alternative value, $\epsilon_{xp} = .4$, as well as a higher alternative value, $\epsilon_{xp} = .8$.

Table 3 summarizes the numerical assumptions, both the values in the base case and alternative values I will use for the purpose of sensitivity analysis. Based on these numerical assumptions, I next calibrate the model's key parameters.

A particularly important step in the calibration process is to determine the expected payoffs for incumbent, startup and agency under the various scenarios (m, c, s). This corresponds to a large set of parameter values. Given the limited amount of data (in particular data regarding consumer utility) I propose a series of assumptions regarding the relation between incumbent profit, startup profit, and consumer surplus. Consider first the values of π_c and μ_c. Suppose that the incumbent faces a linear demand curve $q = \pi_m (2 + \xi - \rho)$,

[14] There is significant variation across AAAM firms, with 0.49% for Alphabet, 4.44% for Amazon, 2.34% for Apple, and 4.10% for Meta.

[15] First, to the extent that the acquirer must pay a price, the gross increase in value, which we will be considering in our calibration, should be augmented by the acquisition price, which is about .5% of incumbent value. Second, one might expect the increase in firm value to be gotten with some lag with respect to the acquisition. If we were to consider, for example, acquisitions in the early part of the 21st century and the lagged growth in market value, then we would obtain substantially higher estimates of growth per acquisition. Third, if some of the targets were s targets (which imply no increase in incumbent value, rather preclude a drop in value), then the value of n used in computing ξ should be lower, resulting in a higher ξ estimate.

[16] For the average value considered, the probability that $\alpha > 1$ is given by 2.06E-9, so truncation does not have much effect on the distribution.

Table 3
Key numerical assumptions.

Description	base	low	high
incumbent's market value	\$200 bn		
c startup's value if not acquired	0		
Increase in incumbent value from c acquisition	0.5%	0.1%	1%
Average value of α (probability of s)	5%	1%	10%
Distribution of α	exponential		
Average acquisition price	\$.49 bn		
Number of potential startups	10,000	1,000	100,000
Number of acquisitions per year	10		
Elasticity of innovation w.r.t. prize	.6	.4	.8
incumbent's Nash bargaining power coefficient	80%	70%	90%

Table 4
Payoffs under complementor acquisition (left table) and under competition between incumbent and startup (right table).

π_c°	$\pi_m\,(2+\xi)^2/4$
θ_c°	p
μ_c°	$\pi_m\,(2+\xi)^2/8$

	$\psi < 3$	$\psi > 3$
π_s°	$\pi_m\,(3-\psi)^2/9$	0
θ_s°	$\pi_m\,\psi^2/9$	$\pi_m\,(1+\psi)^2/4$
μ_s°	$\pi_m\,(3+\psi)^2/18$	$\pi_m\,(1+\psi)^2/8$

where ξ measures the demand shift brought about by integrating the startup with the incumbent, q is quantity and ρ is price.[17] The multiplier π_m ensures that, if $\xi = 0$, then the incumbent's profit remains the same as before the acquisition. Specifically, suppose that the incumbent charges a price ρ for its services. Considering that many of the services offered by AAAM firms are free, one should interpret this price as the value of the inconvenience created by advertising, loss of privacy, etc. Assuming that the incumbent sets this price ρ optimally and that costs are zero, we get the values of π_c and μ_c in Table 4. (The startup's payoff is simply acquisition price.) The linear demand assumption is perhaps a little strong. However, the main purpose of this exercise is to place some discipline on the relation between π and μ, which in this case is $\mu_c^\circ = \frac{1}{2}\,\pi_c^\circ$. Notice that $\xi = 0$ implies $\pi_c^\circ(\xi) = \pi_m$, as one would expect if ξ is to measure the value added by the complementor. I assume that ξ is exponentially distributed with mean $\overline{\xi}$. I calibrate the value of $\overline{\xi}$ based on the equation

$$\pi_m\,(1+0.5\%) = \int \pi_m\,(2+\xi)^2/4\,\exp(-\psi/\overline{\xi})/\overline{\xi}\;d\,\xi \tag{13}$$

where the 0.5% on the left-hand side corresponds to the average increase in incumbent value from acquiring a c startup (cf Table 3). In other words, I assume that there is an exponential distribution of potential complementors, some adding little value, some adding a lot of value, and that, on average, one of such complementors increases incumbent value by .5%.

Consider now the case when the incumbent competes with an s startup. Consider a simple model of Cournot competition with demand $q = \pi_m\,(2-\rho)$. The incumbent's cost is zero, whereas the startup's cost is given by $1-\psi$, where ψ measures the entrant's competitiveness. This formulation explicitly allows for the possibility of ***disruptive innovation***, by which I mean the case when the startup's competitiveness is so drastic that it replaces the incumbent. Specifically, depending on the value of ψ, we get different duopoly solutions. If $\psi = 0$, then the incumbent is effectively a monopolist (in other words, the startup is not a credible competitor). If $\psi = 3$, then the startup is so innovative (disruptive innovation) that it shuts off the incumbent. Values of ψ greater than 3 lead to greater levels of profit and consumer surplus, always with the startup as a monopolist. Specifically, solving the model we get the values in Table 4.

Similar to ξ, I assume that ψ is exponentially distributed with mean $\overline{\psi}$. I calibrate the value of $\overline{\psi}$ so as to fit the average acquisition price for the average value of α under no enforcement. (I assume the observable data is generated by a no-enforcement regime.) Specifically, from (2) I get

$$\overline{p} = (1-\beta)\,\left(\overline{\alpha}\,(\pi_m-\pi_s)+(1-\overline{\alpha})\,(\pi_c-\pi_m)\right)+\beta\,\left(\overline{\alpha}\,\theta_s+(1-\overline{\alpha})\,\theta_m\right) \tag{14}$$

where, for a generic payoff variable $z \in \{\pi,\theta,\mu\}$,

$$z_s = \int z_s^\circ\,\exp(-\psi/\overline{\psi})/\overline{\psi}\;d\,\psi \tag{15}$$

$$z_c = \int z_c^\circ\,\exp(-\psi/\overline{\xi})/\overline{\xi}\;d\,\xi \tag{16}$$

[17] I use ρ for price to avoid confusion with acquisition price p.

Table 5
Calibrated payoff values (base case).

Symbol	Description	value
π_m	incumbent's monopoly profit	$\$200.0 \times 10^9$
π_c	Av. incumbent's profit upon acquiring c target	$\$201.0 \times 10^9$
π_s	Av. incumbent's profit when competing with s	$\$187.3 \times 10^9$
μ_m	Av. Welfare under incumbent monopoly	$\$100.0 \times 10^9$
μ_c	Av. Welfare under c acquisition	$\$100.5 \times 10^9$
μ_s	Av. Welfare under competition	$\$106.7 \times 10^9$
θ_m	Av. startups profit if not acquired	$\$0.0 \times 10^9$
θ_s	Av. startups profit when competing	$\$4.4 \times 10^9$

and the values of z_s°, z_c° are given by Table 4.[18]

Equation (14) includes $\overline{\psi}$ (when we substitute (15) for π_s and θ_s); $\overline{\xi}$ (when we substitute (16) for π_s and θ_s); and $\overline{p}$, $\overline{\alpha}$, π_m and θ_m. The value of $\overline{\xi}$ is given by (13). The values of $\overline{p}$, $\overline{\alpha}$, π_m and θ_m are given in Table 3. We therefore have an (quadratic) equation in $\overline{\psi}$. It admits two solutions, one of which is positive. Basically, the identification strategy is to use actual acquisition prices to obtain the implied values of the potential threat posed by an s entrant. As Bryan and Hovenkamp (2020b) rightly put it, "the acquirer's market power and the transaction value may be useful signals of the risk of harm."

Consider now the cost function, $C(x) = \gamma\, x^\sigma$. From (3), we see that the elasticity of the success rate x with respect to p, the prize from success (under no enforcement), is given by

$$\epsilon_{xp} = \frac{d\ln(x)}{d\ln(p)} = \frac{1}{\sigma - 1}$$

I follow that

$$\sigma = 1 + \frac{1}{\epsilon_{xp}}$$

As to the value of the scaling parameter γ, we have

$$\gamma = \frac{p}{\sigma\, x^{\sigma-1}}$$

Finally, the value of x is calibrated by the ratio of the number of successful startups, 10 per year, divided by the potential number of startups, which I assume is 10,000, that is, $x = .001$.

Table 5 summarizes the results of the calibration exercise, namely the key parameter values that I will use next. Some comments regarding these estimates are in order, in particular the consumer surplus estimates. The value of consumer surplus in the base scenario, $\mu_m = \$100$ bn, is lower than the value implied by Allcott et al. (2020) for Facebook ($31 billion per month in the US only). However, in light of Allcott et al. (2022), there are reasons to believe the $31 bn might overstate μ_m. Brynjolfsson et al. (2019), in turn, estimate that $30 billion per year in consumer surplus in the U.S. alone are created by free internet services. This would suggest a much lower value than $\mu_m = \$100$ bn.

■ **Results.** Fig. 1 summarizes the welfare performance of various alternative merger policies within the family of threshold merger policies. The horizontal axis measures the threshold $\widehat{\alpha}$ above which a merger is blocked. The vertical axis measures expected increase in welfare from a policy with threshold $\widehat{\alpha}$, that is

$$A(\widehat{\alpha}) - \mu_m = \int_0^{\widehat{\alpha}} x_0\,(1-\alpha)\,(\mu_c - \mu_m)\,dF(\alpha) + \int_{\widehat{\alpha}}^{1} x_1\,\alpha\,(\mu_s - \mu_m)\,dF(\alpha)$$

where x_0 is given by (3) and x_1 is given by (6). By definition, the highest value of $A(\widehat{\alpha})$ corresponds to $\widehat{\alpha} = \alpha_o$. As per Proposition 2, $\alpha_h < \alpha_o$, that is, balance of harms is too harsh on mergers. However, as Fig. 1 shows, the loss is welfare from this increase in harshness is not too high, only about 2%.

As per Proposition 1, $\alpha_h < \alpha_p$, that is, balance of harms is harsher on mergers than balance of probabilities. Fig. 1 suggests that the difference is significant in terms of $\widehat{\alpha}$ and in terms of $A(\widehat{\alpha})$. In other words, switching from balance of probabilities to balance of harms would imply a significant decrease in the threshold leading to blocking a merger as well as a significant increase in welfare, about 15%. While the theoretical results do not establish a relation between α_o and α_p, the base simulation suggests that α_o is very close to α_h, and thus and $\alpha_o < \alpha_p$.

Fig. 1 also shows that the welfare difference between balance of probabilities and no enforcement at all is very small. This results from the fact that, for the parameters considered, α is rarely higher than 50%. In fact, $\mathbb{P}(\alpha > .5) = \exp(-.5/.05) = .0045\%$.

[18] One advantage of assuming ξ and ψ are exponentially distributed is that we can obtain (15) and (16) in closed form. The expressions, which are long and not particularly enlightening, can be found in the Appendix.

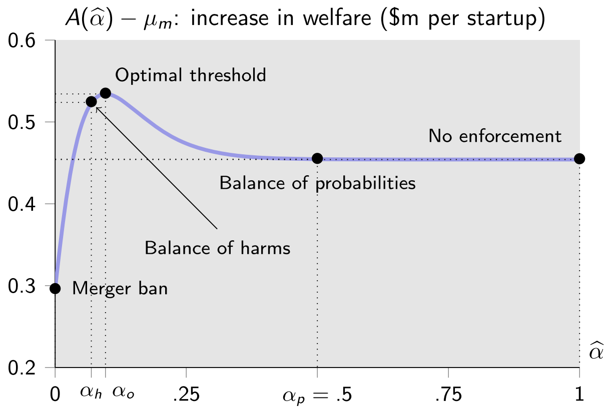

Fig. 1. Balance of harms vs Balance of probabilities. Expected welfare as a function of $\widehat{\alpha}$ (threshold such that mergers are blocked if and only if $\alpha > \widehat{\alpha}$).

Table 6
Expected welfare and other performance measures in base case.

Policy → ↓ Performance measure	Complete ban	Balance of harms	Optimal threshold	Balance of prob's	No enforce't
Welfare per startup ($000)	295.456	523.862	534.197	454.480	454.079
Blocked mergers (%)	100.000	25.090	14.661	0.005	0.000
# successful startups	5.484	8.725	9.115	9.723	9.723
$\mathbb{E}(\alpha)$ successful startups (%)	8.003	5.953	6.047	6.595	6.596
# competitors	0.43887	0.33231	0.26445	0.00064	0.00000

Base case: $\xi = .5\%, \overline{\alpha} = 5\%, \beta = 80\%, \eta = 10^4, \epsilon_{xp} = .6$

Finally, Fig. 1 suggests that imposing a total ban on mergers would imply a significant drop in welfare. Compared to no enforcement, welfare under no mergers is 35% lower. This echoes Furman et al.'s (2019) view that "a presumption against all acquisitions by large digital companies is not a proportionate response to the challenges posed by the digital economy." As we will see next, the drop in welfare resulting from a total ban is primarily due to a significantly lower innovation rate.

The vertical axis in Fig. 1 measures consumer welfare gain, in $m, accrued by a startup (that is, a potential startup). Under no enforcement, the estimated 10,000 startups imply a welfare increase of $4.541bn per year. Given the stratospheric value of big tech firms, this may seem small potatoes. However, we must recall the model is being calibrated to a $200bn incumbent. Seen in this light, $4.541bn represents 4.54% of *discounted* consumer surplus, no small amount.

As mentioned earlier, there is virtually no difference between no enforcement and enforcement by balance of probabilities. A switch from no enforcement to the optimal threshold α_o would imply a consumer welfare increase of 17.6%. A switch to a balance-of-harms policy, α_h, achieves a 15.4% increase in consumer welfare, that is, most of the gain from switching to the optimal policy. Finally, a total ban on mergers, α_b, would imply a 35% decrease in consumer welfare.

One interesting feature of the "horse race" between different alternative merger policies is that their ranking is not uniform across different metrics. Fig. 1 shows the relation in terms of welfare. Table 6 extends this comparison to four other measures: (a) the percentage of potential mergers that are blocked (specifically, the percentage of successful startups whose acquisition would be blocked); (b) the number of successful startups (per period); (c) the average value of α of successful startups (a measure of the *direction* of innovative activity); and (d) the probability of competition, that is, the expected number of successful startups who are not acquired and turn out to be type s. I next discuss these numbers in greater detail.

The second row of Table 6 shows that, if there is no enforcement, then the percentage of blocked mergers under balance of probabilities is only 0.005%, so essentially the same as under no enforcement at all. This is because, as mentioned earlier, the probability that $\alpha > .5$ is given by $\exp(-.5/.1) \approx 0.005\%$. Balance of harms would lead to the rejection of about 25% of the mergers, while the optimal threshold calls for rejecting only the 15% most problematic acquisitions.

The main thrust of the paper is the importance of merger policy in terms of innovation incentives. In this sense, a natural performance measure is the number of successful startups. Consistent with Proposition 3, the third row of Table 6 shows that the number of successful startups (per year, per incumbent) is maximal under no enforcement (as expected from (12)), lower (but approximately equal) under balance of probabilities, lower under the optimal threshold, lower still under balance of harms, and lowest under a complete ban on mergers.[19] When discussing their merger review proposal, Furman et al. (2019) claim that balance of harms "should have a negligible impact on the incentives to invest and innovate associated with the ability to be acquired by a larger company." Table 6 suggests that, compared to the current regime, balance of harms would have more than a marginal effect, specifically, a 9%

[19] Recall that, when calibrating the model, we *assumed* the number of successful startups per period is 10. The reason why the computed value under no enforcement is not equal to 10 is that the calibration was done with the average valeu of α, whereas the value in Table 6 is based on the distribution of α.

Table 7
Expected welfare per potential startup ($m).

Policy → ↓ Parameter	Complete ban	Balance of harms	Optimal threshold	Balance of prob's	No enforce't
base case	295.456	523.862	534.197	454.480	454.079
$\xi = .1\%$	585.434	589.620	590.142	85.569	84.719
$\xi = 1\%$	0.005	2503.279	2503.279	2503.245	2503.279
$\overline{\alpha} = 1\%$	338.653	574.167	583.622	491.447	491.447
$\overline{\alpha} = 10\%$	302.784	514.469	523.614	442.474	420.559
$\beta = 70\%$	127.469	467.428	477.650	466.551	466.390
$\beta = 90\%$	595.649	722.914	726.884	438.046	437.211
$\epsilon_{xp} = .4$	302.043	534.822	539.586	458.009	457.716
$\epsilon_{xp} = .8$	294.478	517.455	535.265	456.064	455.516

Base case: $\xi = .5\%, \overline{\alpha} = 5\%, \beta = 80\%, \eta = 10^4, \lambda = .5, \epsilon_{xp} = .6$

reduction in the innovation rate. That said, this would be more than compensated by greater competition and, overall, would result in greater welfare.

We next consider the average value of α of successful startups. As mentioned in the literature review, a number of papers argue that the prospect of acquisition by a dominant entrant leads startups to bias their research in the direction of projects that are complementary with respect to the incumbent. In terms of our framework, this would imply a low average value of α (of successful startups). It has also been argued that a tougher merger policy might be the solution to counteract that pro-incumbent bias. However, as Proposition 5 shows, this is not necessarily the case. Consistent with this theoretical result, the fourth row of Table 6 shows that the relation between the threshold $\widehat{\alpha}$ and the average α of successful startups, $\mathbb{E}(\alpha)$, is not monotonic. In particular, as we move from balance of probabilities to balance of harms, innovation efforts move in the direction of complementarity with respect to the incumbent. A complete ban on mergers, however, would result in shifting innovation in the direction of higher-α projects.

Finally, when it comes to the number of competitors, we observe, consistent with Proposition 4, that the same ranking as the percentage of blocked mergers: a total ban comes out on top, followed by balance of harms, the optimal threshold, balance of probabilities, and finally no enforcement. The idea is that, as per Assumption 2, the incumbent has more to gain from avoiding competitions than a startup has to gain from challenging the incumbent. As a result, unless a merger is blocked, successful startups are acquired and no competition takes place.

■ **Sensitivity analysis.** Table 7 provides a series of computations that help appraise the sensitivity of the main results with respect to variation in key parameters. The first row reproduces the welfare results in Table 6.

A first remark is that the *size* of the welfare effects varies considerably with some of the parameters. For example, as we vary the value of ξ by one order of magnitude, expected welfare also varies by close to one order of magnitude. This is not particularly surprising or interesting. In this sense, the most relevant aspect of the sensitivity analysis is the relative ranking of the various policy options.

Consider first the case when ξ, the average increase in incumbent's value from acquiring a complement startup, varies from .1% to 1%. The results may be summarized as follows. When ξ is very small, all policies are similar, except for zero enforcement and balance of probabilities, which perform clearly worse. Intuitively, with ξ close to zero, all that a permissive merger policy does is to allow for killer acquisitions. As such, a more restrictive policy is better. By contrast, if ξ is very high, then all policies are similar, except for a total ban, which is clearly worse. Intuitively, most of the welfare gain comes from the incumbent absorbing complementary assets. Therefore, if the values of these assets are very low (resp. high), then a lenient policy (resp. strict policy) performs poorly.

Differently from ξ, variation in $\overline{\alpha}$, the average value of the probability that a startup is a competitor, does not seem to have any significant impact on the level or relative ranking of the various alternatives. At first, one might think that a higher $\overline{\alpha}$ implies a greater likelihood of an s startup and thus the optimality of a stricter merger policy. However, given the equilibrium value of p, a larger $\overline{\alpha}$ also implies that we estimate the surplus value of an s startup is lower. In other words, in line with Bryan and Hovenkamp (2020b), "the acquirer's market power and the transaction value may be useful signals of the risk of harm." In fact, p puts a lot of discipline on our estimate of the harm from killer acquisitions, thus the relative stability of the results with respect to $\overline{\alpha}$.

Consider now variation in β, the incumbent's bargaining coefficient. If we assume the higher value $\beta = 90\%$, then we notice all policies are approximately equivalent, except for no enforcement and balance of probabilities, which are significantly worse. Intuitively, for a given average price paid for a startup acquisition, if the incumbent's bargaining power is greater, this implies that the gain from a killer acquisition must be very high, which in turn also implies that the consumer benefit from blocking such an acquisition is also high.

Finally, we note that the results are not very sensitive to variations in ϵ_{xp}. This is not to say that innovation levels do not change as a result of changes in merger policy. As we saw earlier, the number of successful startups declines considerably as we tighten merger policy. The point is that there are other elements contributing to consumer welfare. In order to get a better idea of what are the main factors, I next consider a counterfactual simulation.

■ **Counterfactual.** There are (potentially) two main forces driving the welfare effects of different merger policies. First, the trade-off between allowing for value-creating mergers and preventing killer acquisitions. Second, the feedback effect that different merger policies have on innovation incentives. In other to get a better understanding of the relative importance of these, I next consider a

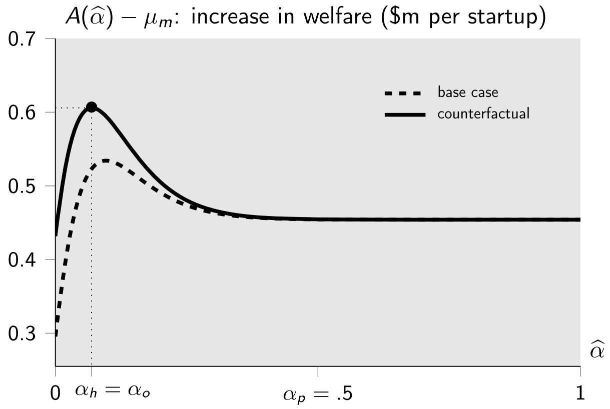

Fig. 2. Welfare as a function of merger policy threshold $\widehat{\alpha}$: base case and counterfactual where innovation effort is fixed at laissez-faire level.

counterfactual where I fix the level of startup investment at the level induced by the belief that no merger will be blocked (and thus that an acquisition will take place at price p with probability 1). Considering the history of the past two decades, this essentially amounts to assuming that a tightening of the merger policy does not have a negative effect on innovation levels as they are currently taking place. Note that I still consider the possibility that x depends on α; I simply disregard the possibility that it reacts to expectations regarding the ability to be acquired.

The results are shown in Fig. 2. In a dashed line, we have the same relation as in Fig. 1 (notice the y axis scale is changed). In a solid line, the counterfactual whereby we fix the value of x at the x_0 level, that is the level corresponding to the belief that a merger will not be blocked. As expected, such belief leads startups to invest more, which in turn leads to higher welfare levels. That said, the qualitative nature of the exercise, as reflected in the shape of the $A(\widehat{\alpha}) - \mu_m$ curve, does not change much.

It is also of note that, in the counterfactual where the value of $x(\alpha)$ is fixed, balance of harms is the optimal threshold level, as shown in Fig. 2. In fact, the reason for the discrepancy between α_h and α_o is precisely the innovation incentive it implies.

We thus conclude that the shape of consumer welfare as a function of the merger threshold does not depend greatly on the feedback effects created by changing innovation efforts. This is not to say that such feedback effects are not important. In fact, as Fig. 2 shows the difference between the red and the blue lines is significant, especially for low values of $\widehat{\alpha}$. In particular, a total ban on mergers would likely lead to a significant decrease in welfare levels, a decrease that would largely be due to the lower innovation incentives implied by eliminating the innovation-for-buyout effect.

5. Discussion

In this section, I consider three issues related to the framework presented in the previous sections: the legal feasibility of balance of harms; the proposal to reverse the burden of proof in a merger; and a model extension that allows for incumbent research effort in addition to startup effort.

■ **Is balance of harms legally feasible?** The Furman report proposed that the UK switch to a balance-of-harms approach to mergers. However, the UK's Competition & Markets Authority (CMA) opined that addressing the challenges of mergers in the digital space "does not require fundamental changes to the existing legislative regime," whereas a shift to a balance-of-harms approach would "bring about a fundamental shift in merger policy" (CMA letter of 21 March 2019). Ultimately, the UK government decided to stick to the current regime, which essentially amounts to something like balance of probabilities.

In Australia, however, there is a precedent for effectively applying an α threshold strictly lower than 50%. Under section 50 of the Competition and Consumer Act 2010 (CCA), mergers are prohibited if they would have the effect, or be likely to have the effect, of substantially lessening competition in the relevant market(s). In two recent mergers, the Australian Competition and Consumer Commission (ACCC) clarified that "likely" in the context of a merger assessment means "a real commercial likelihood" and that this can be lower than a 50% chance. In fact, Paragraph 3.15 of the November 2008 Merger Guidelines states that

> Clearly a substantial lessening of competition must be more than speculation or a mere possibility for it to be likely, but it does not need to be a certainty. Importantly, a substantial lessening of competition need not be 'more probable than not', for the merger to contravene s. 50. Mergers are prohibited when there is a 'real chance' that a substantial lessening of competition will occur.

The calibration exercise presented in the previous section suggests there are considerable gains from switching from a balance-of-probabilities approach to a balance-of-harms approach, a possibility that seems consistent with the Australian approach. By contrast, the US, the UK, and the EU maintain a standard that essentially corresponds to balance of probabilities.

■ **Burden of proof.** In their proposal for merger reform, Scott-Morton et al. (2019) argue that,

> When an acquisition involves a dominant platform, authorities should shift the burden of proof, requiring the company to prove that the acquisition will not harm competition

A similar proposal was made at the US House of Representatives (2020):

> Subcommittee staff recommends that Congress considers shifting presumptions for future acquisitions by the dominant platforms. Under this change, any acquisition by a dominant platform would be presumed anticompetitive unless the merging parties could show that the transaction was necessary for serving the public interest and that similar benefits could not be achieved through internal growth and expansion.

Motta and Peitz (2020) make a similar proposal. Reverting the burden of proof, Scott-Morton et al. (2019) argue, is particularly appropriate when the merging parties have better information than the agency:

> This shifting of the burden of proof from the government (to prove harm) to the parties (to prove benefit) will assist the DA by placing the job of demonstrating efficiencies on the parties, who have a greater ability to know what they are.

A natural way of analyzing the effects of reversing the burden of proof is to consider an extension of the base model whereby, before the attempted acquisition takes place, incumbent and startup learn the actual type of the latter (c or s) but not the agency. In this context, and assuming σ is not very high, we can show that reversing the burden of proof is unambiguously welfare-increasing: mergers would be approved if and only if the target is type c.

This may be a bit too optimistic, however. It assumes that possessing the knowledge that the merger is pro-competitive amounts to overcoming the burden of proof in Court. Considering the US experience, this is hardly the case. If we consider the opposite case, namely $\lambda = 0$, then reversing the burden of proof effectively amounts to banning all mergers, which, as we saw, would likely lead to a significant decline in consumer welfare.

The previous discussion assumes that the incumbent must *always* prove the merger to be pro-competitive. However, the nature of some of the reverse-the-burden proposals is to apply it only when the merger is particularly problematic—in terms of our notation, only when α is particularly high (Scott-Morton et al., 2019). In what follows, I suggest one possible pitfall of this approach.

Suppose that the agency must incur a cost τ in order to block a merger, whereas reversing the burden of proof implies no cost for the agency. Suppose moreover that τ is positive but not much greater than zero. It follows that, when the burden of proof cannot be reversed, instead of applying the balance-of-harms threshold α_h, the agency blocks mergers only when $\alpha > \alpha_c$, where the c in α_c stands for costly blocking of mergers. If τ is positive but relatively small, we get $\alpha_h < \alpha_c < \alpha_o$.

Now suppose that the agency has the option of reversing the burden of proof. Suppose, that $\lambda = 0$, so that reversing the burden of proof effectively implies blocking the merger. It follows that the agency will opt for reversing the burden of proof if and only if $\alpha > \alpha_h$. Since α_h is farther away from α_o than α_c, we conclude that the *option* of reversing the burden of proof implies a more stringent merger policy, to the detriment of consumer welfare.

■ **Incumbent's research effort.** In order to consider the research effort exerted by the incumbent, we augment the timing considered in the base model (see page 3) in the following way: In Step 2, The startup invests $\gamma\, x^\sigma$ in order to innovate with probability x ***and*** the incumbent invests $\gamma\, y^\sigma$ in order to innovate with probability y. Moreover, between Steps 5 and 6, after Nature reveals the target type, one of the following takes place:

- If the startup is type s and was acquired, then the startup's project is discontinued (killer acquisition). If, in addition, the incumbent's project is successful, then the incumbent's project is also discontinued (reverse killer acquisition).
- If the startup is type s and was *not* acquired, then the incumbent's project, if successful, is discontinued (reverse killer acquisition).
- If the target is type c and was acquired, then one of the projects (incumbent or startup) is discontinued (killer or reverse killer acquisition);
- If the target is type c and was *not* acquired, then all successful projects remain active.

The analytical solution of this extended model is considerably more cumbersome than the basic model. We need to consider the four possible combinations of the success probabilities x and y. Moreover, the acquisition price depends on whether the incumbent is successful in its own internal project (as it changes the value of the incumbent's outside option).

Despite this complexity, one can derive the following analytical result: a "softer" merger policy (higher threshold $\widehat{\alpha}$) implies both a lower value of y and a higher probability that a project gets canceled. In other words, a soft merger policy leads to two different manifestations of reverse killer acquisitions. However, once we consider the quantitative estimates based on the extended model, we get similar results. Intuitively, what really matters is the extent to which the acquisition of a c target increases incumbent value. Whether this results from acquiring a new asset, or rather one that might duplicate an internally generated one, makes little difference in terms of consumer surplus. Moreover, to the extent that, with positive probability, there is an inefficient duplication of research efforts, a reduction in y does include a positive component in terms of social surplus.

6. Conclusion

Calibrated models based on aggregate data are not common fare in industrial organization — certainly not as common as they are in macroeconomics. However, considering the scarcity of empirical work on the costs and benefits of different merger policies in the context of big tech, I believe the results of a calibration exercise provide useful information about the sign and the order of magnitude of the main effects.

Specifically, the analysis of the calibrated model of entry and acquisition suggests that moving from balance of probabilities to balance of harms leads to a 15% welfare increase. A complete ban on mergers, in turn, would imply a 35% welfare decrease.

Given the uncertainty about key parameter values, I offer a series of sensitivity analyzes. Some of the key learning points from this exercise are that (a) the results do not depend greatly on the channel provided by ex-ante innovation incentives; and (b) of all calibrated parameters, the average value increase from an acquisition plays a particularly important role.

The first learning point highlights the benefit of a calibration exercise as a means to evaluate the order of magnitude of various effects. In a previous paper (Cabral, 2021), I emphasized the importance of innovation incentives in driving the optimal merger policy. If one is to believe the results from the calibrated model (in terms of orders of magnitude), then one would pay more attention to the dichotomy between pro- and anti-competitive direct effects of the acquisitions rather than the different incentives a merger policy implies for the emergence of new startups. If the present calibration exercise has no other effect, at least it had the effect of changing my mind with respect to Cabral (2021).

The second learning point suggests a promising avenue for future research, namely to model the process of value creation by acquisition and ultimately to estimate the distribution of ξ, a parameter whose value plays a critical role in comparing the effects of alternative merger policies.[20]

To conclude, it is important to mention that, while this paper focuses on merger policy as a “solution” to the big tech problem, merger policy is by no means the only instrument available.[21] First, as argued by Kwoka and Valletti (2021), and notwithstanding the opinion that in some cases it is impossible to “unscramble the eggs,” divestiture can be an important instrument (and an additional reason to increase the $\widehat{\alpha}$ threshold, that is, to ease merger policy). Second, regulation can and should play a bigger role. The argument can be made that vertical restraints and other related exclusionary practices have played a bigger role in cementing the dominance of big tech than acquisitions. And the solution to the abuse of dominant position is to be found in regulation, not merger policy.

CRediT authorship contribution statement

Luís Cabral: Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization.

Appendix A

■ **Expected payoff value under competition.** Computation establishes that

$$\pi_s = \int_0^3 \tfrac{1}{9}\,\pi_m\,(3-\psi)^2\, f(\psi)\,d\psi = \pi_m \left(1 + \tfrac{2}{9}\,\overline{\psi}\,\left(\overline{\psi}\,\left(1 - \exp\left(-3/\overline{\psi}\right)\right) - 3\right)\right)$$

$$\theta_s = \int_0^3 \tfrac{1}{9}\,\pi_m\,\psi^2\, f(\psi)\,d\psi + \int_3^\infty \tfrac{1}{4}\,\pi_m\,(1+\psi)^2\, f(\psi)\,d\psi$$

$$= \pi_m \left(\tfrac{2}{9}\,\overline{\psi} + \tfrac{1}{18}\,\exp(-3/\overline{\psi})\,\left(9\,\overline{\psi}^2 + 32\,\psi + 60\right)\right)$$

$$\mu_s = \int_0^3 \tfrac{1}{9}\,\pi_m\,(3+\psi)^2\, f(\psi)\,d\psi + \int_3^\infty \tfrac{1}{8}\,\pi_m\,(1+\psi)^2\, f(\psi)\,d\psi$$

$$= \pi_m \left(\tfrac{1}{2} + \tfrac{1}{9}\,\overline{\psi}\,\left(3 + \overline{\psi}\right) + \tfrac{1}{36}\,\exp\left(-3/\overline{\psi}\right)\,\overline{\psi}\,\left(12 + 5\,\overline{\psi}\right)\right)$$

Proof of Proposition 1. Follows directly from (10). □

Proof of Proposition 2. Comparing (4) and (7), we conclude that, at $\alpha = \alpha_h$, welfare when allowing the merger is greater than welfare when blocking the merger if and only if x is greater when the merger is allowed. This is because, from (10), $(1-\alpha_h)\,(\mu_c - \mu_m) = \alpha_h\,(\mu_s - \mu_m)$. Comparing (3) and (6), we conclude that x is greater when the merger is allowed if and only if $p > \alpha\,\theta_s + (1-\alpha)\,\theta_m$, which is equivalent to Assumption 2. □

[20] I am grateful to Chiara Ferronato and a referee for asking the question of what additional empirical research would improve the analysis.

[21] One thing that most agree regarding merger policy is the need to go beyond the traditional approach based on market shares and size thresholds. See Wollmann (2019).

Proof of Proposition 3. From Assumption 2, $x_0 > x_1$, where x_0 is given by (3) and x_1 is given by (6). An increase in $\hat{\alpha}$ implies a higher values of x for the values of α within the old and the new α threshold, the same otherwise. The result follows. □

Proof of Proposition 4. An increase in $\hat{\alpha}$ implies that all successful entrants within the interval between old and new threshold are acquired, thus decreasing the number of competitors from a positive value to zero. □

Proof of Proposition 5. Suppose that $\hat{\alpha} = 0$. An infinitesimal increase in α implies an increase in innovation effort for infinitesimal values of α. Since average α of successful startups is strictly positive, it follows that the average values of α decreases as $\hat{\alpha}$ increases. The opposite reasoning applies for a decrease in $\hat{\alpha}$ starting from $\hat{\alpha} = 1$. □

Data availability

Data will be made available on request.

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