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 system, at least in the EU) to balance of harms (the new UK approach) leads to a 15% welfare increase. A complete ban on mergers, in turn, would imply a 65% 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 very robust to changes in key parameters. I consider some extensions of the basic framework, including reverting the burden of proof of pro-competitive effects.

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1. Introduction

Digital industries — or whatever definition includes GAFAM (Google, Amazon, Facebook, Apple, Microsoft) — 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).

And while the dominant platforms collectively acquired several hundred startups from 2000-2020, antitrust agencies did not block a single one of these transactions. 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, at least in the EU) to balance of harms (the new UK approach) leads to a 15% welfare increase. A complete ban on mergers, in turn, would imply a 65% 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% being blocked, which in turn would imply an additional 2% increase in welfare.[1]

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

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.

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, Schmutzler, and Seibel (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 has 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, Ederer, and Ma (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, Rajan, and Zingales (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, Motta, and Tarantino (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 "authorisation 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. Bryan and Hovenkamp (2020a) show that startups are biased toward inventions that help improve the leader's 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, Motchenkova, and Dijk (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."

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, Celik, and Tian (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, Roldan-Blanco, and Schmitz (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.

There are also a few empirical retrospective analyses 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, Leccese, and Wagman (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.[2]

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) in the whole process by allowing or blocking such acquisitions. The main goal of the paper is to understand the interplay between these three stages of the process, in particular 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, de Montjoye, and Schweitzer's (2019) observation that it "is frequently difficult to distinguish pro-competitive or neutral deals from anti-competitive deals."[3] Specifically, the timing of the game is as follows:

1. Nature generates a value of α from $F(\alpha)$
2. The startup chooses the innovation rate x
3. The incumbent and the startup negotiate an acquisition price p
4. The merger authority decides whether to allow the merger to take place
5. The target type (s or c) becomes common knowledge and payoffs are received

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 will), the startups' choices effectively determine the direction of innovative activity of the "system" as a whole. 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.

2. Calvano and Polo (2021) offer a survey of innovation issues in digital markets.
3. 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)	$(\pi_m - p, p, \mu_m)$

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 take 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 has a weight $1-\beta$). This assumption reflects the evidence from the digital space of great asymmetry in bargaining power between incumbent and startup.[4]

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.[5]

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.

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 happen in two different ways: First, a potential complement who is not acquired (and does not affect the incumbent's payoff). Second, a potential competitor who is acquired (a so-called killer acquisition). (A third possibility, which I don't need to model explicitly,

4. 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.
5. 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.

is that innovation fails to take place.)

I make the following assumption regarding payoff values:

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

Basically, this implies that the incumbent is best off when acquiring a complement and worse off when competing against one. I note that the 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. 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.

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 $\pi_m - \pi_s$.

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. 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.[6] 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 (and recently implemented) by the UK's Competition and Markets Authority, 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.[7]

All of the four merger policies listed above have one thing in common: they are all based on a threshold $\widehat{\alpha}$ 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 $\widehat{\alpha}$ 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***: $\widehat{\alpha} = 1$
- ***complete ban***: $\widehat{\alpha} = 0$
- ***balance of probabilities***: block merger when $\alpha > .5$
- ***balance of harms***: block merger when $\alpha\,\mu_s + (1-\alpha)\,\mu_m > \alpha\,\mu_m + (1-\alpha)\,\mu_c$
- ***optimal policy***: value of $\widehat{\alpha}$ that maximizes ex-ante welfare

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 GAFA eco-system so as to be more precise about the "horse race" between the above merger policies.

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

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

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

6. According to Federico, Morton, and Shapiro (2020), 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.
7. In Section 5, I consider additional alternative merger review schemes, including reversal of burden of proof and approval with probability $\phi \in (0,1)$.

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
$f(\xi)$	distribution of startup's value conditional on being type c (Section 4)
$f(\psi)$	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
ϕ	probability that acquisition is approved (Section 5)
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 $z \in \{0, 1, p, h, r\}$
Other	
β	incumbent's acquisition bargaining weight
γ, σ	parameters of innovation cost function

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

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

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 will ever take place, the startup picks x so as to solve

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

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

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

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." Furman et al. (2019) seem to be in agreement:

> At present, merger assessment only considers how likely a merger is to reduce competition. If a substantial lessening of competition is more likely than not to result, a merger may be blocked.

In terms of the present framework, this would seem to imply that a merger is approved if and only if $\alpha < 50\%$.[8] It follows that

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

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, "under the system as it stands [in the UK and in the EU], the CMA could only block the merger if it considered the smaller company more likely than not to be able to succeed as a competitor." This, they argue, "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. Similarly, Bourreau and de Streel (2019) recommend that

8. The most recent case reaffirming this view is CK Telecoms UK Investments Ltd (Case T-399/16). Paragraph 116 of the Judgment of the General Court (28 May 2020) states: "It is therefore in the light of the economic outcome attributable to the concentration which is the most likely to ensue that the Commission must, as a following step, show that that concentration would probably and significantly impede effective competition in the relevant market." I am grateful to Pierre Larouche for pointing this out to me.

> The Courts should ... move from a 'more likely than not' standard to a standard that takes the risks and the costs of antitrust error equally into account.

In terms of my model, a "balance of harms" approach corresponds to approving 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 blocking the merger. In fact, (9) may be re-written as

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

In other words, the balance of harms approach consists in blocking mergers when the likelihood that the target is type s exceeds a threshold α_h. It follows that

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

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, 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. 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

$\alpha(\mu_c - \mu_m) > (1-\alpha)(\mu_c - \mu_m)$. However, the value of x is not invariant with respect to merger policy. In fact, anticipating a merger will be blocked, a startup invests less in research. Specifically, x, given by (6) when the startup anticipates an acquisition will be blocked, is lower than the value, given by (3), when the startup anticipates an acquisition will not be blocked. We thus get the following result:

Proposition 2. $\mathbb{E}(x)$ *is strictly increasing in* $\widehat{\alpha}$

The threshold α_h was determined based on ex-post welfare considerations, that is, taking the value of x is given. Our next result focuses on the difference between the subgame perfect equilibrium, as described by (10), and the ex-ante optimal threshold, α_o.

Proposition 3. $\alpha_h < \alpha_o$

In words, the ex-post optimal threshold, α_h, is lower than the ex-ante optimal threshold, α_o. Or, to put it differently, 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 3, 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 shown by Proposition 2.

Similar results to Proposition 3 may be found in Mason and Weeds (2013), Jaunaux, Lefouili, and Sand-Zantman (2017), and Gilbert and Katz (2022).[9] Proposition 3 is reminiscent of a similar result from 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 3 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 a second-order effect on incentives. The comparative statics of Proposition 3 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.

Figure 1 illustrates Proposition 3 and the analysis so far. All three panels measure the threshold $\widehat{\alpha}$ on the horizontal axis. The top panel shows welfare for a given value of x. The two (straight) lines show expected welfare (over the baseline μ_m) if the merger is approved, $(1-\alpha)(\mu_c - \mu_m)$; as well as expected welfare (over the baseline μ_m) if the merger is blocked, $\alpha(\mu_s - \mu_m)$. This panel shows the essence of balance of harms. If a merger is approved, welfare increases if the target turns out to be type c. If it is type s, then the merger stifles welfare-increasing competition. By contrast, if a merger is blocked then welfare increases if the target turns out to be type s. If it is type c, then blocking the merger foregoes the benefit of a value-increasing acquisition.

The balance of harms approach means that a merger should be blocked if and only if the expected benefit from blocking (red line) exceeds the expected benefit from allowing the merger (green line). This results in a threshold α_h.

9. But see Sørgard (2009) for the opposite case.

Figure 1
Balance of harms and optimal threshold

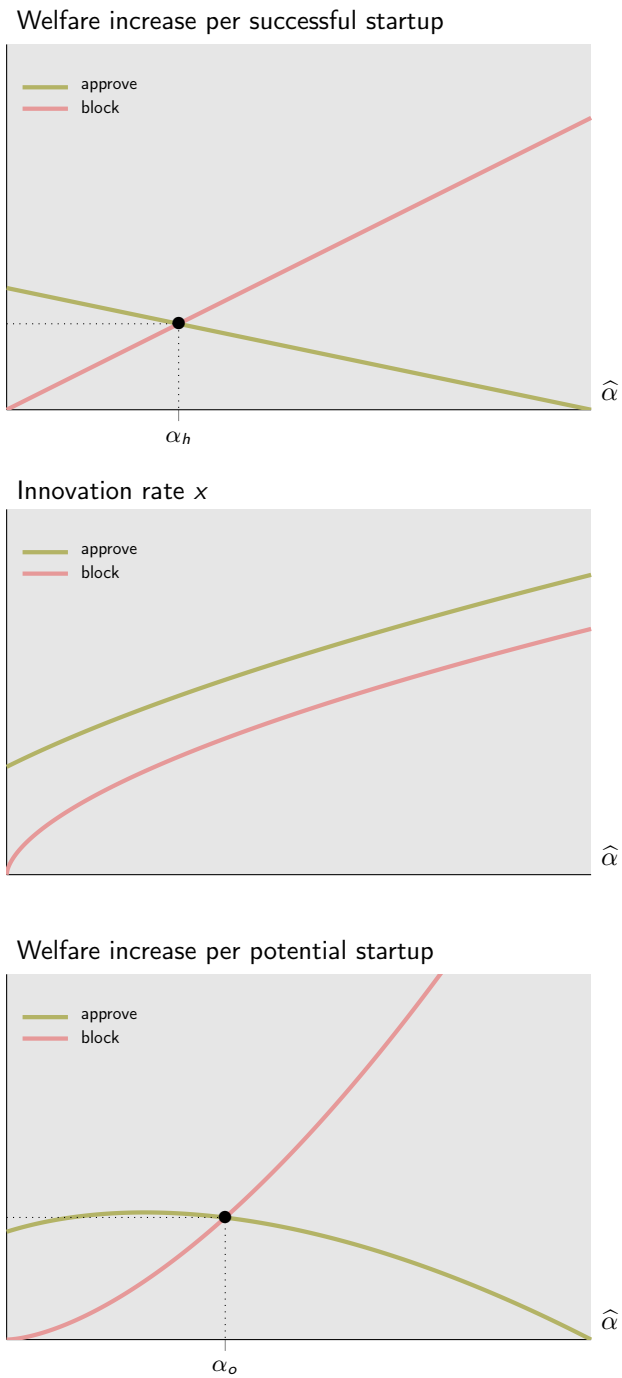


Table 3
Acquisitions and stock value, decade starting January 2010. Facebook data for Jan 2013 – Dec 2019. Sources: Wikipedia, macrotrends.com

Company	Market value Jan 2010 ($ bn)	Market value Dec 2019 ($ bn)	Number of acquisitions	MV growth per acquisition (%)
Amazon	58.25	933.74	64	4.44
Apple	190.40	1,296.82	83	2.34
Facebook	68.62	594.92	54	4.10
Google	392.10	934.64	177	0.49

The balance of harms approach (implicitly) assumes that the innovation rate is given. However, as we saw earlier, the value of x when the startup anticipates the merger will be allowed, given by (3), is greater than the value of x when the startup anticipates the merger will be blocked, given by (6). In fact, from (3) and (6), $x_0 > x_1$ if and only if $p > \alpha\,\theta_s + (1-\alpha)\,\theta_m$, which is equivalent to Assumption 2. This is illustrated in the middle panel of Figure 1, which shows that, especially for low values of α, blocking a merger implies a large percent cut in the innovation rate.

Taking into consideration the effect that merger policy has on the innovation rate, the optimal policy balances not just the costs and benefits of merger approval given a value of x, but also the effect it has on the innovation rate. This is done in the bottom panel of Figure 1. The expected value from approving the merger is the product of the green line in the top panel (decreasing in $\widehat{\alpha}$) and the green line in the middle panel (increasing in $\widehat{\alpha}$), resulting in a concave green line in the bottom panel. The expected value from blocking the merger is the product of the red line in the top panel (increasing in $\widehat{\alpha}$) and the red line in the middle panel (also increasing in $\widehat{\alpha}$), resulting in a convex red line in the bottom panel. Similar to the top panel, we derive the optimal threshold as the point with the two lines cross, namely α_o. As per Proposition 3, we find that this threshold is greater than the balance-of-harms threshold.

In sum, we conclude that $\alpha_h < \alpha_p$ and that $\alpha_h < \alpha_o$. How large are these differences? How much do they matter from a welfare point of view? In the next section, I attempt to calibrate the model based on a variety of data and moments from GAFA.

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 quantititve estimate of the performace of different alternative merger policies. Specifically, I calibrate the model developed in the previous section to be broadly consistent with one of the GAFA firms. As a starting point, I assume market valuation provides a good estimate of the incumbent's discounted annual profits. Specifically, I assume $\pi_m = \$200\,\text{bn}$, where profit values are measured as the present value of future profit streams. I should note that the value of π_m serves exclusively as a scaling factor. As such, it does not have any influence on the ordering of alternatives.

Next, I consider the increase in value from acquiring a complementor. Table 3 shows the evolution of market value by the GAFA firms during the decade starting in 2010 (in the case of Facebook, during the 2013–2019 period). For example, from 2010–2020 Amazon acquired 66 targets and its market cap increased from \$58 bn to \$934 bn. Naturally, much if not most of this growth was internal growth. However, if we assume that all of this growth in valuation resulted from acquisitions, this would correspond to an increase of $\sqrt[64]{933.74/58.25} \approx 1.0444$, or 4.44% per acquisition. Similar calculations lead to the values of the rightmost column in Table 3.

There are reasons to believe that the value increase resulting from acquisitions is higher or lower than this value. First, as already mentioned, much of firm growth is internal growth, which suggests that the value increase resulting from acquisitions is lower than the values in the right column of Table 3. Second, 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. Third, 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. Finally, if some of the acquisitions are killer acquisitions, then the increase in value per c type acquisition is under-estimated by the rightmost column in Table 3. In fact, by assumption, the acquisition of an s type firm leads to a decrease in market value given by the acquisition price.

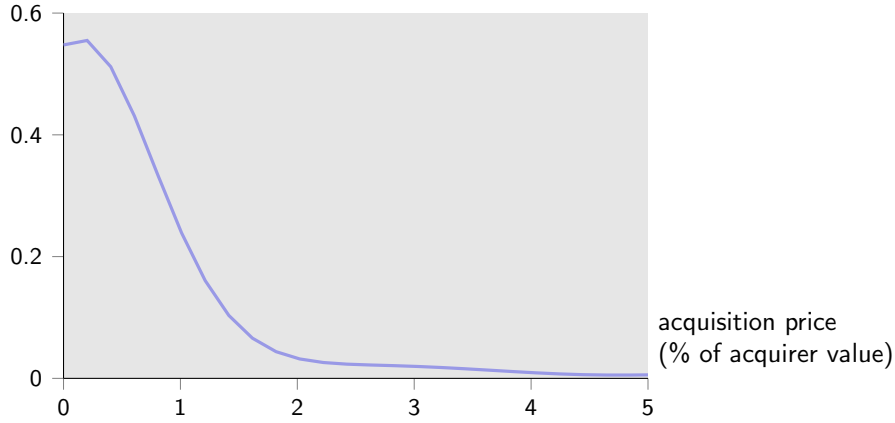
All things considered, I assume that the average increase in value due to an acquisition that complements the incumbent's assets is equal to 0.5% of the acquirer's value. Given the importance of this parameter, I consider an alternative lower value1 of 0.1% and an alternative higher value of 1%.

I assume the average price of an acquisition is \$490 m. I obtain this value as follows. I collect all of the Google's acquisitions for which a price is listed on Wikipedia. I then divide the acquisition price by Google'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, Leccese, and Wagman (2022), \$1.4 bn. However, it should be noted that the market cap of GAFA 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 5% and truncated at 1, so that $\alpha \in [0, 1]$.[10] This is consistent with the idea that the vast majority of acquisitions have been of type c rather than of type s targets. As Furman et al. (2019) put it, "the majority of acquisitions by large digital companies are likely to be either benign or beneficial for consumers, though a minority may not be." If, from an ex-ante point of view, we define a killer acquisition as the acquisition of a firm with $\alpha > .5$ (in the sense of balance of probabilities), then $\overline{\alpha} = .05$ implies that the probability of such a potential acquisition is given by $\mathbb{P}(\alpha > .5) = \exp(-.5/.05) = .0045\%$. If, from an ex-post point of view, we define killer acquisitions as acquisitions of s firms, then $\overline{\alpha} = .05$ implies that 5% of acquisitions (under no enforcement) are killer acquisitions. Gautier and Lamesch (2021) examine the 175 acquisitions by GAFAM during the 2015–2017

10. 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.

Figure 2
Acquisition price as a percentage of acquirer value at time of acquisition. Source: Wikipedia



period and report that most are discontinued post acquisition. However, it is difficult to decide whether this corresponds to a killer acquisition, a failed acquisition, or an acquisition that was motivated by a specific asset owned by the target.[11] 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. 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 if 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 values in Table 3, which imply an annual average of 9.5 acquisitions.

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 GAFA 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.

11. In a previous version of the paper, they argued 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 $1/175 \approx 0.6\%$, which falls within the .0045%–5% range.Cunningham, Ederer, and Ma (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.

Table 4
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%

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 4 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 is to determine the expected payoffs for incumbent, startup and agency under the various scenarios (m, c, s). Consider first the values of π_c and μ_c. Suppose that the incumbent faces a linear demand curve $q = \pi_m (2 + \xi - \rho)$, where ξ measures the demand shift brought about by integrating the startup with the incumbent, q is quantity and ρ is price.[12] 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 GAFA 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 5. (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

12. I use ρ for price to avoid confusion with acquisition price p.

Table 5
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°	$\pi_m\,(3+\psi)^2/18$	$\pi_m\,(1+\psi)^2/8$

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

$$\pi_m\,(1+0.5\%) = \int \pi_m\,(2+\xi)^2/4\exp(-\psi/\overline{\xi})/\overline{\xi}\,d\,\xi \tag{12}$$

where the 0.5% on the left-hand side corresponds to the average increase in incumbent value from acquiring a c startup (cf Table 4).

Consider now the case when the incumbent competes with 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 5.

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

$$\overline{p} = (1-\beta)\left(\overline{\alpha}\,(\pi_m-\pi_s) + (1-\overline{\alpha})\,(\pi_c-\pi_m)\right) + \beta\left(\overline{\alpha}\,\theta_s + (1-\overline{\alpha})\,\theta_m\right) \tag{13}$$

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

$$z_s = \int z_s^\circ \exp(-\psi/\overline{\psi})/\overline{\psi}\,d\,\psi \tag{14}$$

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

and the values of z_s°, z_c° are given by Table 5.[13]

Equation (13) includes $\overline{\psi}$ (when we substitute (14) for π_s and θ_s); $\overline{\xi}$ (when we substitute (15) for π_s and θ_s); and $\overline{p}$, $\overline{\alpha}$, π_m and θ_m. The value of $\overline{\xi}$ is given by (12). The values of

13. One advantage of assuming ξ and ψ are exponentially distributed is that we can obtain (14) and (15) in closed form. The expressions, which are long and not particularly enlightening, can be found in the Appendix.

Table 6
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	$\$4.4 \times 10^9$

$\overline{p}$, $\overline{\alpha}$, π_m and θ_m are given in Table 4. 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 follows that

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

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

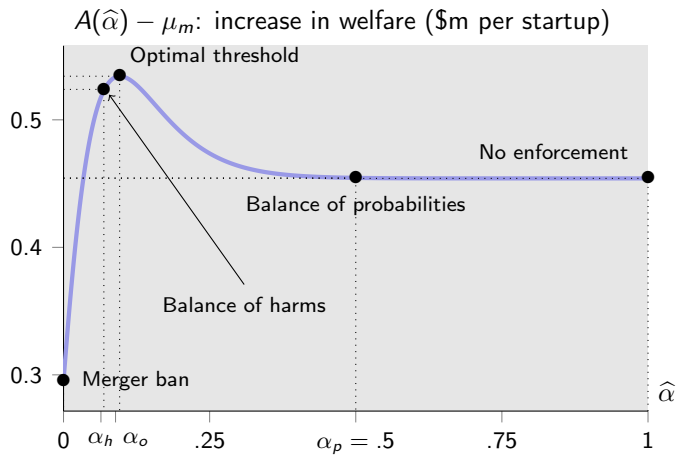
$$\gamma = \frac{p}{\sigma\, x^{\sigma-1}}$$

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 6 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, Gentzkow, and Song (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.** Figure 3 summarizes the welfare performance of various alternative merger policies within the family of threshold merger policies. The horizontal axis measures the

Figure 3
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 $\alpha > \widehat{\alpha}$)



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

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

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 3, $\alpha_h < \alpha_o$, that is, balance of harms is too harsh on mergers. However, as Figure 3 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. Figure 3 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%.

Figure 3 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, as mentioned on page 15, $\mathbb{P}(\alpha > .5) = \exp(-.5/.05) = .0045\%$.

Finally, Figure 3 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.

One interesting feature of the "horse race" between different alternative merger policies is that their ranking is not uniform across different metrics. Figure 3 shows the relation in terms of welfare. Table 7 extends this comparison to four other measures: (a) the percentage of potential mergers that are blocked (specifically, the percentage of successful startups whose

Table 7
Expected welfare and other performance measures in base case

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

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

acquisition would be blocked); (b) the number of successful startups (per period); (c) the average value of α of successful startups; 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 7 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. The third row of Table 7 shows that the number of successful startups (per year, per incumbent) is maximal under no enforcement (as expected from Proposition 2), 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.[14] 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 7 suggests that, compared to the current regime, balance of harms would have more than a marginal effect, specifically, a 9% 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

14. 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 7 is based on the distribution of α.

Table 8
Expected welfare per potential startup ($m)

Policy → Scenario ↓	Zero enforcement	Balance of harms	Balance of probabilities	Optimal threshold	Total ban
base case	454.079	523.862	454.480	534.197	295.456
$\xi = .1\%$	84.719	589.620	85.569	590.142	585.434
$\xi = 1\%$	2503.279	2503.279	2503.245	2503.279	0.005
$\overline{\alpha} = 1\%$	491.447	574.167	491.447	583.622	338.653
$\overline{\alpha} = 10\%$	420.559	514.469	442.474	523.614	302.784
$\beta = 70\%$	466.390	467.428	466.551	477.650	127.469
$\beta = 90\%$	437.211	722.914	438.046	726.884	595.649
$\epsilon_{xp} = .4$	457.716	534.822	458.009	539.586	302.043
$\epsilon_{xp} = .8$	455.516	517.455	456.064	535.265	294.478

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

policy might be the solution to counteract that pro-incumbent bias. However, as Table 7 shows, 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 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 8 provides a series of computations that help estimate the sensitivity of the main results with respect to variation in key parameters. The first row reproduces the welfare results in Table 7.

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. 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. 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 is 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.

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}.

5. Extensions

In this section, I consider two extensions of the framework presented in the previous sections: noisy policy and the proposal to reverse the burden of proof in a merger.

■ **Noisy merger policy.** Up until now, we considered a merger policy based on a threshold, namely a threshold $\widehat{\alpha}$ such that a merger is blocked if and only if $\alpha > \widehat{\alpha}$. Consider now the possibility that, at Stage 4 (cf Page 4), the acquisition of an α startup is blocked with probability $\phi \in [0, 1]$. Anticipating this merger policy, the startup chooses x so as to solve

$$\max_x \; x\left(\phi\left(\alpha\,\theta_s + (1-\alpha)\,\theta_m\right) + (1-\phi)\,p\right) - \varsigma\,x^2$$

which leads to

$$x = \left(\frac{\phi\left(\alpha\,\theta_s + (1-\alpha)\,\theta_m\right) + (1-\phi)\,p}{\gamma\,\sigma}\right)^{\frac{1}{\sigma-1}}$$

where p is given by (2). Finally, agency welfare is given by

$$\begin{aligned} A &= (1-x)\,\mu_m + x\left(\phi\left(\alpha\,\mu_s + (1-\alpha)\,\mu_m\right) + \left(1-\phi\right)\left(\alpha\,\mu_m + (1-\alpha)\,\mu_c\right)\right) \\ &= \mu_m + x\left(\phi\,\alpha\,(\mu_s - \mu_m) + \left(1-\phi\right)\,(1-\alpha)\,(\mu_c - \mu_m)\right) \end{aligned} \tag{16}$$

My main result in this context is that, for some values of α, the agency is better off by approving a merger with at strictly interior probability ϕ:

Proposition 4. *Let $\alpha_o \in (0, 1)$ be the $\widehat{\alpha}$ threshold that maximizes welfare. If $\alpha = \alpha_o$, then welfare is highest when the merger is approved with probability $\phi \in (0, 1)$.*

Intuitively, at $\alpha = \alpha_o$, the benefits from committing to block a merger ($\phi = 0$) are equal to the benefits from allowing a merger ($\phi = 1$). Blocking the merger leads to a higher level of

welfare (given x) but a low value of x. Allowing the merger to go through, leads to a high level of x but a low level of ex-post welfare. In between, ex-post welfare varies linearly with ϕ and x varies approximately linearly with ϕ too. Since welfare is given by x times ex-post welfare, expected welfare is a product of the type $x\,(1-x)$, that is, a concave function that has its maximum in (0,1).

How much does welfare increase in practice once we allow for a strictly interior approval probability $\Phi(\alpha)$? For our base case, it can be shown that $\Phi(\alpha)$ is zero for low values of α and 1 for high values of α, with a transition path from 0 to 1 at around $\alpha = \alpha_o$. Expected welfare under this alternative policy is given by \$561 k, which is 5% higher than the optimal threshold (with "pure strategies") and 7% higher than balance of harms.

I should add, however, that the model with "pure strategies" under-estimates the degree of noise in the review process. In this sense, it's quite possible that a threshold policy like balance of harms, considering the level of legal uncertainly inherent in "real world" review processes, adds noise in the eyes of the startup to an extent that it effectively achieves the gains predicted by Proposition 4.

■ **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 consider 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.

We next consider the possibility of asymmetric information and the proposal of reverting the burden of proof. Specifically, we now consider the following game timing:

1. Nature generates a value of α from $F(\alpha)$
2. The startup chooses the innovation rate x
3. With probability λ, Nature gives the incumbent knowledge of the target's type
4. The incumbent and the startup negotiate acquisition price p

5. The merger is allowed if and only if the incumbent can show the target's type to be of type c
6. The target type (s or c) becomes common knowledge and payoffs are received

Suppose that the incumbent learns the nature of the target and that the target is of type c. Then acquisition price solves

$$\max_{p} \ (\pi_c - p - \pi_m)^{\beta} \left(p - \theta_m\right)^{1-\beta}$$

which implies

$$p = (1-\beta)\,(\pi_c - \pi_m) + \beta\,\theta_m \tag{17}$$

Suppose instead that the incumbent learns that the target is of type s or, alternatively, does not learn anything about the target other than that it is type s with probability α. Then, as per the burden of proof rule, no merger is allowed. (I will later consider an alternative version when there is a safe-harbor $\widehat{\alpha}$ threshold.) If no merger is allowed, then the startup's expected payoff is θ_s (if it's known that the startup is of type s) or $\alpha\,\theta_s + (1-\alpha)\,\theta_m$ (if the startup's type remains unknown).

All in all, at Stage 1, the startup expects a payoff of $\alpha\,\theta_s + (1-\alpha)\,\theta_m$ except when information is revealed regarding its type (probability λ) and the type is c (probability $1-\alpha$). If this happens, then the startup expects an *additional* payoff of $p - \theta_m$. Putting it all together, the expected prize from successful innovation is given by

$$\begin{aligned} &\alpha\,\theta_s + (1-\alpha)\,\theta_m + \lambda\,(1-\alpha)\left(p - \theta_m\right) = \\ &= \alpha\,\theta_s + (1-\alpha)\,\theta_m + \lambda\,(1-\alpha)\,(1-\beta)\,(\pi_c - \pi_m - \theta_m) \end{aligned}$$

Let us next turn to the startup's problem. The value of x solves

$$\max_{x} \ x\left(\alpha\,\theta_s + (1-\alpha)\,\theta_m + \lambda\,(1-\alpha)\,(1-\beta)\,(\pi_c - \pi_m - \theta_m)\right) - \gamma\,x^{\sigma}$$

which leads to

$$x_r = \left(\frac{\alpha\,\theta_s + (1-\alpha)\,\theta_m + \lambda\,(1-\alpha)\,(1-\beta)\,(\pi_c - \pi_m - \theta_m)}{\gamma\,\sigma}\right)^{\frac{1}{\sigma-1}} \tag{18}$$

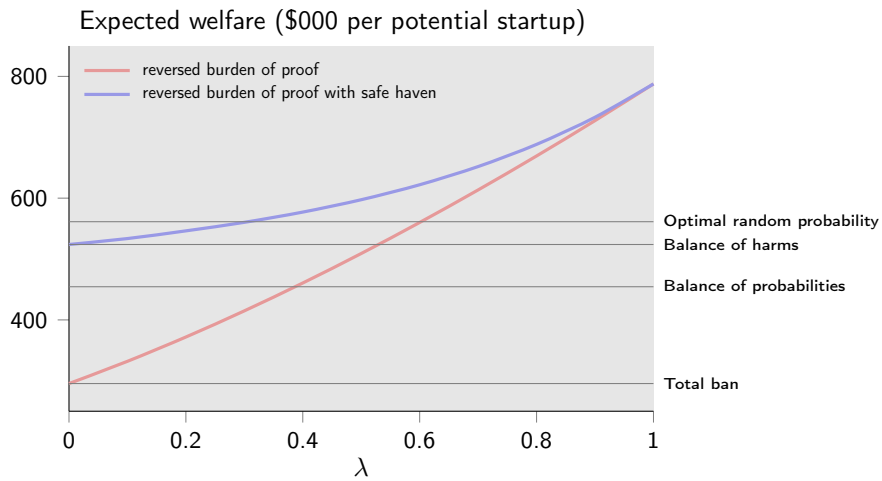
Finally, welfare is given by

$$\begin{aligned} A_r &= (1-x)\,\mu_m + x\left(\alpha\,\mu_s + (1-\alpha)\,(1-\lambda)\,\mu_m + (1-\alpha)\,\lambda\,\mu_c\right) \\ &= \mu_m + x\left(\alpha\,(\mu_s - \mu_m) + \lambda\,(1-\alpha)\,(\mu_c - \mu_m)\right) \end{aligned} \tag{19}$$

where r stands for "reversal of burden of proof." Does reversing the burden of proof increase welfare? The next result provides sufficient conditions for an affirmative or a negative answer.

Proposition 5. *(a) There exist $\lambda' \in (0,1)$ and $\sigma' > 1$ such that, if $\lambda > \lambda'$ and $\sigma < \sigma'$, then agency payoff under reversed burden of proof is greater than under balance of harms.*
(b) There exists $\lambda' \in (0,1)$ such that, if $\lambda < \lambda'$, then then agency payoff under reversed burden of proof is lower than under balance of harms.

Figure 4
Welfare under reversal of burden of proof as a function of λ.



At one extreme, if the merging parties have complete information about the nature of the merger and are able to prove it in Court, then reversing the burden of proof is superior than balance of harms, for the simple reason that it eliminates type I and type II errors in merger review. At the opposite extreme, if the likelihood that the merging parties have the required information to make their case in Court is low, then reversing the burden of proof is essentially equivalent to banning mergers, which, as we have seem leads to lower welfare than balance of harms.

■ **Reverse burden of proof with a safe haven.** When explaining the details of their proposed merger reform, Scott-Morton et al. (2019) argue that

> Mergers between dominant firms and substantial competitors or uniquely likely future competitors should be presumed to be unlawful, subject to rebuttal by defendants.

This is different from what we considered before. The idea is that reversal of the burden of proof only applies to acquisitions of "uniquely likely future competitors." One way to model this is to assume that the reversal of burden of proof applies only to mergers with $\alpha > \alpha_r$. We next consider a policy whereby mergers with $\alpha < \alpha_r$ are allowed (safe haven), whereas mergers with $\alpha > \alpha_s$ are presumed unlawful and require the merging parties to prove pro-competitive efficiencies. The subgame-perfect value of α_r is given by the equality

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

The left-hand side measures expected welfare from allowing the merger to go through. The right-hand side measures expected welfare from requiring proof of competitiveness. With probability α, the target is type s, in which case no merger takes place (regardless of whether the merging parties are or are not informed about the target type). With probability $(1-\alpha)$, the target is type c. Then the merger takes place with probability λ (incumbent is able to prove competitiveness), whereas with probability $(1-\lambda)$ the initial value of μ_m remains.

This results in a threshold

$$\alpha_r = \frac{(1-\lambda)(\mu_c - \mu_m)}{(1-\lambda)(\mu_c - \mu_m) + (\mu_s - \mu_m)}$$

where r stands for reversing the burden of proof. Figure 4 plots expected welfare under the two versions of reversal of burden of proof considered above, with a safe haven (blue) or without a safe haven (red). The figure is based on the base case considered in the calibration in the previous section. Also plotted on the figure are the welfare levels of the various threshold policies (which do not depend on λ, and thus correspond to horizontal gray lines).

The red line illustrates Proposition 5. If λ is sufficiently high, then welfare is greater than under balance of harms. By contrast, if λ is sufficiently low, then welfare is lower than under balance of harms. In fact, as λ tends to zero, welfare tends to the level corresponding to a total ban on mergers.

The blue line illustrates the case of reversed burden of proof with a safe haven, that is, the case when mergers with $\alpha < \alpha_r$ are allowed and the presumption of unlawfulness only applies to mergers with α_r. As $\lambda \to 0$, $\alpha > \alpha_r \to \alpha_h$ and we get the same welfare level as under balance of harms. As λ increases, however, welfare under reversed burden of proof increases as well, and is greater than under balance of harms. In fact, for high enough λ, welfare is greater under reversed burden of proof than under an optimal threshold α_o.

How low is a low λ? Figure 4 shows that it takes λ lower than about 30% in order for an optimal commitment to $\widehat{\alpha}$ to perform better than reversing the burden of proof (with a subgame-perfect safe haven). Is 30% low? Although I model λ as the probability that the incumbent possesses superior information, in reality this should be understood as the product of two different probabilities: the probability of having the information and the probability of successfully making the case in Court. In this regard, it seems reasonable to assume that the value of λ is relatively low. That said, one might also add that reversing the burden of proof is superior to balance of harms, though for low values of λ the difference is small.

6. Conclusion

The analysis of the calibrated model of entry and acquisition suggests that moving from balance of probabilities (the current system, at least in the EU) to balance of harms (the new UK approach) leads to a 15% welfare increase. A complete ban on mergers, in turn, would imply a 65% welfare decrease.

Since the implementation of the new UK system (balance of harms), the first acquisition by a large platform was finally blocked in 2021. The CMA ruled that Meta must divest from Giffy, a firm it had acquired 19 months earlier for a reported $400 million. This was a first not just for the UK but also globally: the first startup acquisition by a dominant platform blocked by an agency. Comparing the real-world dynamics of this and related cases with the theoretical framework in this and other academic papers, a few notes are in order. First, in addition to the uncertainty modeled by α, there is also considerable legal uncertainty: The guidelines approved by the CMA are quite broad and there will always be gray areas in the evaluation of the α of a given acquisition. In some ways, this is good: as Proposition 4 shows, some uncertainty about the agency's threshold may actually increase welfare. The

problem with legal uncertainty is that it exacerbates the commitment problem, possibly beyond the level of sub-optimality characterized by Proposition 3.

The commitment issue is also problematic when it comes to the proposal of reversing the burden of proof. If the agency can commit to a safe have threshold, then reversing the burden of proof (for mergers with high α) is an improvement over simply deciding based on that threshold. However, once we allow the agency to opt for reverting the burden of proof, the temptation to exercise the option can be high, in particular considering how short-staffed agencies are. And if Courts are as favorable to defendants as they tend to be in the US, it is quite possible that reverting the burden of proof will effectively translate into something close to a complete ban on mergers, a policy which we predict would have disastrous consequences.

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.[15] 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.

15. 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).

Appendix

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

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

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

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

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

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

Proof of Proposition 1: Follows directly from (10). ■

Proof of Proposition 2: Anticipating a merger will be blocked, a startup succeeds with probability x_0, given by (3). Anticipating a merger will be blocked, a startup succeeds with probability x_1, given by (6). The expected valeu of x is given by

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

Assumption 2 implies that $x_0 > x_1$. It follows that $\mathbb{E}(x)$ is strictly increasing in $\widehat{\alpha}$.■

Proof of Proposition 3: Comparing (4) and (7), we conclude that, at $\alpha = \alpha^*$, 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), $(1-\alpha^*)\,(\mu_c - \mu_m) = \alpha^*\,(\mu_s - \mu_m)$. 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. ■

Proof of Proposition 5: Consider first part (a). Suppose that $\lambda = \sigma = 1$. Since $\sigma = 1$, the value of x is invariant with respect to merger review (it is either 0 or 1). It follows that welfare is greater under reversed burden of proof if and only if expected payoff (conditional on x) is greater. Under balance of harms, welfare given x is given by $\max\{\alpha\,\mu_m + (1-\alpha)\,\mu_c, \alpha\,\mu_s + (1-\alpha)\,\mu_m\}$. Since $\lambda = 1$, under reversed burden of proof, welfare given x is given by $\alpha\,\mu_s + (1-\alpha)\,\mu_c$. Since $\alpha\,\mu_s + (1-\alpha)\,\mu_c > \alpha\,\mu_m + (1-\alpha)\,\mu_c$ and $\alpha\,\mu_s + (1-\alpha)\,\mu_c > \alpha\,\mu_s + (1-\alpha)\,\mu_m$, it follows that welfare (conditional on x) is greater under reversed burden of proof. The first part of the result then follows by continuity.

Consider now part (b). Suppose that $\lambda = 0$. This implies that, under reversed burden of proof, no merger is allowed. For $\alpha > \alpha_h$, this leads to the same outcome (including the same value of x) as under balance of harms. For $\alpha < \alpha_h$, however, this leads to lower agency payoff than under balance of harms. The second part of the result then follows by continuity. ■

Proof of Proposition 4: If a merger is approved with probability ϕ, then welfare is given by (16), that is,

$$A = \mu_m + x\left(\phi\,\alpha\,(\mu_s - \mu_m) + \big(1-\phi\big)\;(1-\alpha)\,(\mu_c - \mu_m)\right)$$

Computation establishes that $d^2 A / d\phi^2 = 2\,(1-\beta)\,\Omega_1\,\Omega_2$, where

$$\begin{aligned}\Omega_1 &= \alpha\,(\mu_s - \mu_m) - (1-\alpha)\,(\mu_c - \mu_m)\\ \Omega_2 &= \alpha\,\theta_s + (1-\alpha)\,\theta_m - \big(\alpha\,(\pi_m - \pi_s) + (1-\alpha)\,(\pi_c - \pi_m)\big)\end{aligned}$$

Ω_1 is strictly increasing in α. From (10), $\alpha = \alpha_h$ implies $\Omega_1 = 0$. Proposition 3 implies that $\alpha_o > \alpha_h$. We conclude that $\Omega_1 > 0$ when $\alpha = \alpha_h$. Assumption 2 implies that $\Omega_2 < 0$. We conclude that $d^2 A / d\phi^2 < 0$. By definition, $A\,|_{\alpha\,=\,\alpha_o,\,\phi\,=\,0} = A\,|_{\alpha\,=\,\alpha_o,\,\phi\,=\,1}$. Since A is continuously differentiable in ϕ and $d^2 A / d\phi^2 < 0$, it follows that there exists a $\phi \in (0,1)$ that maximizes A. ■

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