KILL ZONE

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ABSTRACT

We study why high-priced acquisitions of entrants by an incumbent do not necessarily stimulate more innovation and entry in an industry (like that of digital platforms) where customers face switching costs and enjoy network externalities. The prospect of an acquisition by the incumbent platform undermines early adoption by customers, reducing prospective payoffs to new entrants. This creates a "kill zone" in the space of startups, as described by venture capitalists, where new ventures are not worth funding. Evidence from changes in investment in startups by venture capitalists after major acquisitions by Facebook and Google suggests this is more than a mere theoretical possibility.

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There is a growing worry that digital platforms (multi-sided markets that offer digital services to customers, often for free, in exchange for data) might be gaining market power, distorting competition, and slowing innovation. A specific concern is that such platforms might acquire any potential competitors, dissuading others from entering, and thus preventing innovation from serving as the competitive threat that is traditionally believed to keep monopoly incumbents on their toes. In a sense, such platforms create a "Kill Zone" around their areas of activity. For instance, Albert Wenger, a managing partner at Union Square Ventures and an early investor in Twitter recently declared the "Kill Zone is a real thing. The scale of these companies [digital platforms] and their impact on what can be funded, and what can succeed, is massive."[1] Consistent with this idea, Figure 1 shows that the number and the dollar value of new start-ups in the social media space have dropped dramatically in the last few years.

Yet, this decline in the raw numbers could be driven by other concurrent factors. Most importantly, the idea that acquisitions discourage new investments is at odds with a standard argument in economics (see Phillips and Zhdanov (2013), and for related evidence); if incumbents pay handsomely to acquire new entrants, why should entry be curtailed? Why would the prospect of an acquisition not be an extra incentive for entrepreneurs to enter the space, in the hope of being acquired at hefty multiples?

In this paper we argue that this standard economic argument relies critically on the value at which firms are acquired being adequate compensation for innovation. This may not hold in the context of acquisitions by digital platforms, because the economics of digital platforms differ significantly from the neoclassical economics of firms taught in standard textbooks. To show this, we build a simple model of platform competition that contains the key novel ingredients present in this space: First, they are two-sided in that one side faces advertisers while the other side provides customers a service, which is often priced at zero. As a result, there isn't any price competition on the customer side. Second, there are important network externalities on the customer side of the market. Third, some customers face switching costs.

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[1] https://promarket.org/google-facebooks-kill-zone-weve-taken-focus-off-rewarding-genius-innovation-rewarding-capital-scale/ . Also see the Economist (2018) https://www.economist.com/business/2018/06/02/american-tech-giants-are-making-life-tough-for-startups, *Assessing the Impact of Big Tech on Venture Investment*, OLIVER WYMAN (July 11, 2018), https://www.oliverwyman.com/content/dam/oliver-wyman/v2/publications/2018/july/assessing-impact.pdf, and Ian Hathaway, *Platform Giants and Venture-Backed Startups*, IAN HATHAWAY BLOG (Oct. 12, 2018), http://www.ianhathaway.org/blog/2018/10/12/platform-giants-and-venture-backed-startups

In this context we show that a crucial role in the success of an innovation is played by early adopters amongst customers, whom we shall term "techies". Techies choose their favored platform mainly for its technical characteristics, and have the incentive to uncover the underlying quality of each rival platform. The mass of early techie adopters, in turn, drives the adoption by ordinary non-techie customers for two reasons. First, the mass of techie adopters offers a signal about the fundamental quality improvement brought about by the new platform. Second, this mass creates a network externality for ordinary customers, who have to choose whether to adopt the new platform.

Consider the decision of techies. They care primarily about the fundamental technical quality of the platform. However, they also engage deeply in any technology, so they have high switching costs (of learning every minor aspect of any platform they adopt). If techies expect two platforms to merge, they will be reluctant to pay the switching costs and adopt the new platform early on, unless the new platform significantly outperforms the incumbent one. After all, they know that if the entering platform's technology is a net improvement over the existing technology, it will be adopted by the incumbent after merger, with new features melded with old features so that the techies' adjustment costs are minimized. Thus, the prospect of a merger will dissuade many techies from trying the new technology. By staying with the incumbent, however, they reduce the stand-alone value of the entering platform.

The stand-alone market value of the entering platform is driven both by its perceived quality and the total number of customers who adopt it (because of network externalities). Yet, this number depends crucially on the number of techies who adopt it, which in turn depends on the expectation this platform would indeed stand alone. Since the stand-alone value represents the entrant's reservation value in any merger negotiation with the incumbent, the prospect of a future acquisition can sufficiently reduce adoption by techies and thus the entrant's payoff so as to discourage more entry.[2]

Put differently, think of early-adopter as bees: in pursuing their own interest they generate a positive externality. Because of this externality, any environmental condition that affects bees' incentives to roam across flowers has a much bigger effect than its direct effect on

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[2] There is a parallel here to exclusionary conduct. If everyone expects the incumbent to use exclusionary contracts (or other anticompetitive behavior) to prevent customers from leaving, this expectation alone will decrease the value of any new entrant. In turn, this will discourage entry. The point here is that the exclusionary conduct may simply occur by the very nature of online platforms, network externalities, and switching costs.

bees' welfare. The same is true here. Any environmental condition that reduces the techies' incentives to search for better platforms and switch to them has a negative effect on the system. By contrast, any environmental condition that increases the techies' incentives to search for better platforms and switch to them has a positive effect on the system.

If it is so important for an entrant to signal that she will not sell out to the incumbent, why doesn't she commit to it? An entrant entrepreneur will try her best to portray fierce independence, committing to uphold the "purity" of her new technology. In fact, the often-claimed presence of super egotistic CEOs/founders, driven more by a vision than by money, can be interpreted as an attempt to commit credibly to never sell the platform. Nevertheless, in a world of rational agents, it is hard to see how the entrepreneur can credibly commit not to sell when selling maximizes her profits (given that a monopolist's profits are greater than the sum of the profits of two duopolists). This is where antitrust enforcement can help. If a large incumbent is prevented by regulation from acquiring new platforms operating in a similar space, then entrant entrepreneurs are credibly committed not to sell. This commitment will increase the valuation of new entrants, stimulating investments in technological improvements and entry.

From a welfare point of view, these restrictions on mergers will have costs: if the market remains segmented, network externalities will be lower than otherwise achievable, and some customers will not enjoy a superior technology. If the market eventually converges to the superior technology, too many customers would have to pay the switching costs. Thus, the social optimum will not be an outright prohibition or complete laissez faire, but some middle-of-the road policy, which will trade off the ex-post welfare losses produced by merger restrictions against the ex-ante gains in investments in innovation.

Let us turn to evidence. Since companies are reluctant to engage in acquisitions that will be blocked by antitrust, the announcement of an acquisition signals that antitrust authorities are likely to allow acquisitions in a certain space. Under this assumption, a counter-intuitive implication of our model is that acquisitions of new entrants at generous multiples by incumbent digital platforms can lead to a decrease in new entry and a decrease in the amounts invested in similar businesses at similar stages of development.

The novelty of the phenomenon and the paucity of acquisitions by large incumbent platforms do not allow an in-depth analysis. Nevertheless, we check whether the limited data available are consistent with the model. We collect data on the number of deals and dollar

amounts invested by the venture capitalist in specific sectors, after major acquisitions by Facebook and Google are announced. We find that normalized VC investments in start-ups in the same space as the company acquired by Google and Facebook drop by over 40% and the number of deals falls by over 20% in the three years following an acquisition. In comparison, a similar calculation for other acquisitions in the software industry suggests that normalized VC investments in start-ups in the same space as the company acquired goes up (not down) by over 40 percent, while the number of deals goes up slightly in the three years following an acquisition. The software industry seems to follow the standard economic argument suggested by Phillips and Zhdanov (2013), while the platform acquisitions seem very different.

We consider alternative explanations of these results, including the possibility that most (if not all) the start-ups similar to the ones acquired by Google or Facebook were created with the only objective of being acquired by Google or Facebook. Thus, when a tech giant chooses another target, the potential alternatives lose their likely buyer and thus financing. To address this concern, we only look at startups that are in a similar space, but not too close to the space of the acquired ones (so that they cannot be considered perfect substitutes). Our results are if anything stronger. We also consider the possibility of the acquired start-up being a complement rather than a substitute to the incumbent platform.

While this limited evidence can only be considered suggestive, it is consistent with the most counterintuitive implications of the model. It would be premature to draw any policy conclusion on antitrust enforcement based solely on our model and our limited evidence. Yet, our model can help us think what other type of policies may increase innovation in digital platforms, if the concerns about a "kill zone" are warranted. For example, the more an incumbent can freely copy the technological innovations of new entrants, the worse the incentives of early adopters to switch to a new entrant will be. These reduced incentives will lower the stand-alone valuation of new entrants and thus lower the return to innovation. This result is not specific to digital platforms: the ability to copy freely an innovation always reduces the incentives to invest. What is new is the extent of the problem. In the usual setting, the incumbent's ability to copy reduces, but does not eliminate, the profitability of the innovator. In our setting, if the incumbent can freely copy the new features of an entrant, the new entrant will be left with insignificant profits since no one will switch.

Importantly, innovation increases if we increase interoperability across platforms (i.e., we make network externalities available to all). With interoperability, the new entrant obtains the incumbent's network externalities. Consequently, competition primarily focuses on the intrinsic quality differences, increasing the return to innovation. If there is a policy conclusion to be drawn from our model, it is this: interoperability across platforms helps resolve many of the distortions in digital platforms because it reduces the incumbency advantage from network externalities and switching costs.

Schumpeter (1934, 1942) are, of course, the seminal works on incentives to innovate and competition. He noted, among other effects, the possibility that the incumbent monopolist has a lower incentive to innovate for fear of cannibalizing its existing technology, a higher incentive to innovate for fear of losing the monopoly entirely, and a greater incentive to innovate given the size of the market it has access to. Aghion et al. (2005) subsequently argue for an inverted U shaped relationship between competition and innovation.

The classic analysis of the effect of antitrust enforcement on incentives to innovate is Segal and Whinston (2007). In their model, where there are no network externalities, voluntary licensing agreements (and equally mergers) raise both parties' payoffs and thus increase innovation. In this framework, Cabral (2018) introduces the distinction between radical innovation (competition for the market) and incremental innovation (competition within the market). He shows that antitrust restrictions on acquisitions (or technology transfers) can lead to lower incremental innovation but higher radical innovation. The negative impact of mergers on radical innovation, however, comes from an "opportunity cost" effect. By increasing the payoff of incremental innovation, mergers reduce the additional payoff of radical innovation. In our model we have only radical innovation. Nevertheless, mergers can reduce the incentive to innovate because of the impact they have on the difficulty of attracting customers away from the incumbent.

On the empirical side, Phillips and Zhdanov (2013) provide evidence consistent with the idea that a more active market for mergers and acquisitions encourages innovation by small firms, while enabling larger firms to optimally outsource R&D to them. By contrast, Seru (2014) finds that firms acquired in diversifying mergers tend to reduce the scale and novelty of R&D activity relative to potential targets that escaped being acquired. He finds that the effect is centered around inventors becoming less productive after mergers, and associates it with the

centralized nature of conglomerates reducing incentives to innovate. Phillips and Zhdanov reconcile their results with Seru's by arguing that large firms (such as conglomerates) have lower incentives to innovate, and prefer acquiring innovative small firms, and this may be an appropriate division of labor. Our paper, of course, focuses on a subset of acquisitions – specifically, acquisitions by platforms – and explains why the analysis and outcomes may be different there.

Cunningham, Ederer, and Ma (2019) examine acquisitions by pharmaceutical companies and find that acquired drug projects are less likely to be taken to full development when they overlap with the acquirer's existing drug portfolio, especially when the acquirer faces limited competition and has a long time to expiry on existing drug patents. While such "killer acquisitions" may stop further R&D on competing products and pre-empt future competition, they may also reduce resultant product quality. Cunningham et al. do not focus on how this alters ex ante incentives to innovate, the central concern in our work.

Another related paper is Wen and Zhu (2019). They examine how app developers on the Android mobile platform alter efforts as the threat of Google's entry increases. They find that developers reduce innovation and raise prices (in an attempt to milk their value before actual Google entry) for the affected apps. They also find developers shift efforts to unaffected areas. Of course, their focus is not on acquisition but on competition from the platform. Relatedly, a number of policy papers assess the costs and benefits of platform acquisitions (see, for example, Bourreau and de Streel (2019) and Hylton (2019)).

In the law literature, a number of scholars have focused on the unique attributes of online platforms in necessitating a rethink of antitrust law and practice. Khan (2019) argues that platform owners control access to customers and when they sell services on the platform, have a special ability to foreclose competitors. Wu (2019) argues that a variety of network products compete for customer attention, and ought to be seen as competitors when traditional antitrust theory would ordinarily dismiss any competitive link. In a similar vein, we focus on the network externalities and switching costs associated with online platforms to argue why they could have substantial impact.

Finally, Bryan and Hovenkamp (2020) present a theory of competition amongst innovating firms and find that start-ups are biased towards innovations that help the leader increase its lead after acquisition (which eventually diminishes competition and innovation as the leader's

advantage increases) rather than help a follower catch up (which would increase the competitive pressure in the industry to innovate). They argue that mandating compulsory licensing of new technologies when the startup's acquirer is dominant in the industry may help preserve competition and incentives for startups to innovate. Unlike us, their focus is not on industries where there are two sided platforms with network externalities. Our work should be thought of as complementary to theirs.

The rest of the paper proceeds as follows. We outline the model in section 1, describe the data in section 2, report the results in section 3, discuss possible extensions in section 4, and conclude in section 5.

1. The Model

The difficulty in modeling customer choice, when it is influenced by network externalities is the possibility of multiple equilibria – if I believe everyone will switch to an entrant, I have an incentive to switch, and if I believe no one will switch, I will not switch. To finesse this problem, we use the technique of global games (for an excellent overview, see Morris and Shin (2003)).

1.1 Set-Up

Consider an incumbent platform I, which is threatened by a new entrant platform E. Without loss of generality, we will assume the quality of the incumbent is normalized to zero. The quality increment of the new entrant, θ, is realized from an uniform distribution $\left[\underline{\theta}, \overline{\theta} \right]$, where $\underline{\theta} \leq 0 < \overline{\theta}$. There are two groups of customers: *techies* with measure λ and *ordinary customers* with measure 1. We consider two periods and three dates with date t denoting the end of period t.

Techies are early adopters. At date 0 (the beginning of the first period), techies observe a public signal $q = \theta + \varepsilon$ about E's quality increment relative to I, where ε is random noise, distributed normally with mean 0 and precision α. Having observed the signal, the techies decide whether to switch to the new entrant or not. For the techies, the per-period incremental utility of switching is driven entirely by the incremental technical quality of the platform (i.e., they do not benefit from network externalities, which we will define shortly). If they switch, techies need to spend time to understand the new technology thoroughly, so each techie *i* faces a one-time

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switching cost s_i to move to the new platform.[3] Techie switching costs are uniformly distributed over $[0, \overline{s}]$. The future is assumed discounted at a gross interest rate of 1, and all agents are risk neutral, expected utility maximizers.

At date 1, the two companies decide whether to merge or not. The share of the merged value each party gets is determined through a bargaining process we will specify shortly. If they do merge, the superior technology – which is the entrant's if $\theta > 0$ -- will be adopted by the merged entity and all the customers will enjoy it, regardless of whether they had switched before or not. The acquirer in the merger ensures a smooth transition to all customers so that switching costs are minimized thereafter (to zero). If the two companies do not merge, they will survive $n \geq 1$ periods independently – think of this period as the lifecycle of the technology.

Ordinary customers do not have sufficient information to switch in the first period. In the second period, they are confronted with the decision of whether to switch only if the merger fails to go through. Their switching decision is not based only on the expected technical characteristics of the new platform, but also on the number of customers (techie and ordinary) a platform is able to attract/retain. Thus, ordinary customers do experience some network externalities. Specifically, for an ordinary customer the benefit of a platform is given by the sum of its expected quality and the total measure of consumers (techie and ordinary) who opt for it.

At the beginning of period 2, ordinary customers have two pieces of information in making their switching decision: i) they observe how many techies switched in period 1 [4]; ii) they also see a private signal of incremental entrant quality, $x_i = \theta + \eta_i$, where η_i is random noise, distributed normally with mean zero and precision β. For simplicity, ordinary customers have no switching costs, though these are easily handled. They also do not switch again in the future, after this initial switching decision. The timeline is as follows.

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[3] Equivalently, since the techie's utility from switching is $q - s_i$, s_i could be the techie's private signal about quality.

[4] Practically, this may reflect the volume of buzz in the market (or lack of it) about the product, and write-ups by the tech correspondents of various newspapers, magazines, or informative websites.

Date 0   Date 1   Date 2...

Techies see q and   Incumbent and entrant   Customers stay with
decide whether to   decide whether to merge   the choices they
switch based on their   and the terms thereof.   made at date 1.
own switching cost   If merger does not take
                           place, ordinary customers
                           decide whether to switch.

What we now determine is the measure of techies that switch, and its anticipated effect on switching behavior by ordinary customers if the merger does not take place. This will then affect the target price that the incumbent will offer the entrant to merge. We postpone discussion of the merger till the next subsection.

1.2 Analysis of Switching Behavior

In making their decision at date 0, techies know that if they switch they will enjoy a product of quality q for $(1+m)$ periods, where $m=0$ if the merger takes place at date 1, and $m=n$ if it does not. As a result, each techie will decide to switch comparing this benefit with her personal cost of switching. Thus, she will switch if and only if

$$(1+m)q > s_i.$$

Given that techies' switching cost is uniformly distributed, the measure of techies who switch in the first period is given by $\lambda\dfrac{(1+m)q}{\bar{s}}$ if $0\leq\dfrac{(1+m)q}{\bar{s}}\leq 1$, 0 if $\dfrac{(1+m)q}{\bar{s}}<0$ and λ otherwise. To simplify the notation in the rest of the paper we will assume that $0\leq\dfrac{(1+m)q}{\bar{s}}\leq 1$.[5] Clearly, the longer the period m that the firms will remain independent, the more each techie who switches enjoys the incremental quality of the entrant, and the more the fraction of techies who find it worthwhile to incur switching costs. The measure of techies who remain with the incumbent is $\lambda[1-\dfrac{(1+m)q}{\bar{s}}]$.

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[5] We avoid having to deal with truncated expressions with this assumption, but it changes nothing material.

After the first period, ordinary customers observe how many techies have switched. Since they know *m*, they can back out *q*, the techies' public signal. Combining with the private signal x_i they observe at the beginning of period 2, each ordinary customer *i* will have a posterior belief of the quality differential with mean $\rho_i = \dfrac{\alpha q + \beta x_i}{\alpha + \beta}$ and precision $\alpha + \beta$. Assuming the merger has not taken place, the ordinary customer's decision to switch depends upon (i) his posterior belief of the quality differential between platforms and (ii) his estimate of the size of customers who will choose each platform and provide network externalities. He will switch if and only if the network-externality-adjusted quality of the entrant is superior, that is, iff

$$\rho_i + p(\rho_i) + \frac{(1+m)\lambda q}{\underline{s}} \geq (1 - p(\rho_i)) + \left(\lambda - \frac{(1+m)\lambda q}{\underline{s}}\right),$$

The first term on the left hand side is his perception of the quality differential, the second is his measure $p(\rho_i)$ of ordinary customers he believes will switch to the entrant based on his perception of the quality differential, and the third term is the measure of techies who have already switched. The second and third term thus represent the network externalities realized from switching. The first term on the right hand side is the measure of ordinary customers he believes will not switch, and the second is the measure of techies who have not switched. The sum represents the network externalities from staying with the incumbent. This inequality can be rewritten as

$$\rho_i + 2(p + \frac{(1+m)\lambda q}{\underline{s}}) - (1 + \lambda) \geq 0.$$

1.2 The Switching Game

The ordinary customer's decision is typical in a global game (see, for example, Morris and Shin, 2000, 2003), and allows us to obtain unique equilibria.[6] To solve it, we first conjecture that ordinary customers will follow a switching strategy where they switch if their prior of quality exceeds a threshold ρ^*. When an ordinary customer at the cusp of switching observes a signal x_i (and thus has a posterior belief $\rho_i = \rho^*$) and chooses to switch, he will have to assume that a

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[6] We structure it as a global game to obtain a unique solution. Without the global game structure, we would have to focus on a specific equilibrium.

fraction p will switch as well, i.e. a fraction p should have a posterior at least as high as his.

Since $\Pr\{\rho_j > \rho_i \mid \rho_i\} = 1 - \Pr\{\rho_j \leq \rho_i \mid \rho_i\}$, we need to determine the probability that $\rho_j \leq \rho_i$.

Conditional on ρ_i, x_j will be distributed with a mean ρ_i and a precision $\dfrac{1}{\dfrac{1}{\alpha+\beta}+\dfrac{1}{\beta}} = \dfrac{\beta(\alpha+\beta)}{\alpha+2\beta}$.

Thus, we can write $\Pr\{\rho_j \leq \rho_i \mid \rho_i\} = \Pr\{\dfrac{\alpha q + \beta x_j}{\alpha+\beta} \leq \rho_i \mid \rho_i\} = \Pr\{x_j \leq \rho_i + \dfrac{\alpha}{\beta}(\rho_i - q) \mid \rho_i\} =$

$\Pr\{\eta_j \leq \rho_i + \dfrac{\alpha}{\beta}(\rho_i - q) - \theta \mid \rho_i\}$. But since $\theta \mid \rho_i = \rho_i$, this equals

$$\Pr\{\eta_j \leq \dfrac{\alpha}{\beta}(\rho_i - q) \mid \rho_i\} = \Phi\big(\gamma(\rho_i - q)\big)$$

where Φ is the cumulative standard normal distribution and $\gamma = \sqrt{\dfrac{(\alpha+\beta)}{(\alpha+2\beta)}\dfrac{\alpha^2}{\beta}}$.

For $\rho^i = \rho^*$ to be the switching threshold, a necessary condition is that

$$\rho^* + 2(p(\rho^*) + \dfrac{(1+m)\lambda q}{\overline{s}}) - (1+\lambda) = 0$$

or

$$\rho^* + 2(1 - \Phi\big(\gamma(\rho^* - q)\big) + \dfrac{(1+m)\lambda q}{\overline{s}}) - (1+\lambda) = 0$$

(1) $\qquad \rho^* + 2 + 2\dfrac{(1+m)\lambda q}{\overline{s}} - (1+\lambda) - 2\Phi\big(\gamma(\rho^* - q)\big) = 0$.

Let $S(\rho) = \rho + 2 + 2\dfrac{(1+m)\lambda q}{\overline{s}} - (1+\lambda) - 2\Phi\big(\gamma(\rho - q)\big)$. For $\rho^i = \rho^*$ to be the switching

equilibrium, it should be the case that $S(\rho)$ is increasing in ρ given the parameters (q, m).

Theorem 1: For $\gamma < \sqrt{\dfrac{\pi}{2}}$ the function $S(\rho)$ is always increasing in ρ given (q, m) and there is a

unique switching equilibrium.

Proof: Given (q, m) the function $S(\rho)$ is always increasing in ρ if $\dfrac{dS(\rho)}{d\rho} > 0$

$$\frac{dS(\rho)}{d\rho} > 0 \implies 1 - (2\gamma)\phi\big(\gamma(\rho - q)\big) > 0$$

$$\phi\big(\gamma(\rho - q)\big) < \frac{1}{2\gamma}$$

$$\frac{1}{\sqrt{2\pi}} \exp\left\{\frac{-(\gamma(\rho - q))^2}{2}\right\} < \frac{1}{2\gamma}$$

$$(\rho - q)^2 > \frac{-2}{\gamma^2} \ln(\frac{\sqrt{2\pi}}{2\gamma})$$

This condition will always hold for $\gamma < \sqrt{\frac{\pi}{2}}$. Then, $S(\rho)$ is always increasing in ρ and hence

the optimal switching point ρ^* is the only solution of $S(\rho) = 0$.

QED

The following figure shows the variation of optimal switching point for $\lambda = 0.4$, $\bar{s} = 4$, $\alpha = 300$, $\beta = 100$, $\theta \in [0,1]$.

For a given *n*, we can see that as the public quality signal for early switchers, *q*, increases, the optimal switching point for ordinary customers decreases. Furthermore, for a given *q*, the optimal switching point decreases as the number of subsequent periods *n* increase since more techies switch for any given *q*.

Optimal Switching Point for λ = 0.4
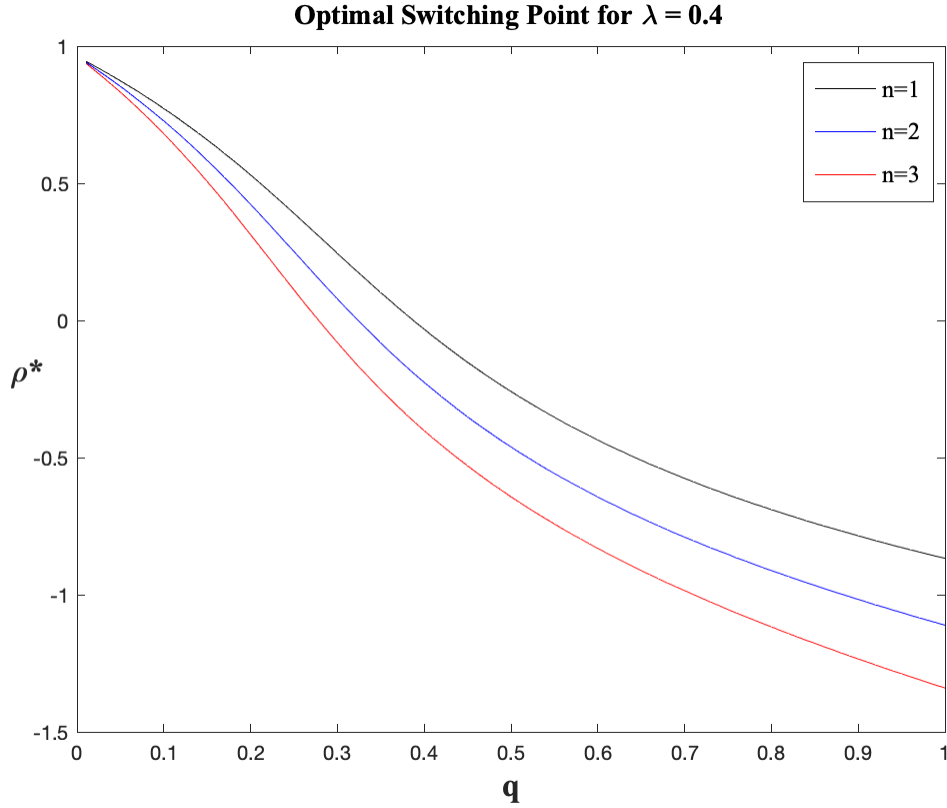
This chart immediately suggests the following corollaries:

Corollary 1: The optimal switching point decreases and the fraction of ordinary customers switching to the new technology increases in the number of periods *(1+m)* that the techie expects the entrant to remain independent.

Proof: Total differentiation of $S(\rho^*) = 0$ given q:

$$\left(1-(2\gamma)\phi\left(\gamma(\rho^*-q)\right)\right)d\rho^* + 2\frac{\lambda q}{s}dm = 0$$

$$\frac{d\rho^*}{dm} = \frac{-2\dfrac{\lambda q}{s}}{\left(1-(2\gamma)\phi\left(\gamma(\rho^*-q)\right)\right)} < 0 \text{ if } \gamma < \sqrt{\frac{\pi}{2}}$$

Intuitively, the longer the period the firms will remain independent, the more techies will switch to the entrant for a given positive public signal *q*, increasing the network externalities associated with the entrant. In turn, this will reduce the quality threshold at which ordinary customers will switch to the entrant if the merger did not take place, enhancing the expected value of the entrant as a stand-alone entity.

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Corollary 2: The optimal switching point decreases and the fraction of ordinary customers switching to the new technology increases with a higher public signal.

Proof: Total differentiation of $S(\rho^*) = 0$ given m:

$$\left(1 - (2\gamma)\phi\left(\gamma(\rho^* - q)\right)\right)d\rho^* + \left(2\frac{(1+m)\lambda}{\bar{s}} + (2\gamma)\phi\left(\gamma(\rho^* - q)\right)\right)dq = 0$$

$$\frac{d\rho^*}{dq} = \frac{-2\dfrac{(1+m)\lambda}{\bar{s}} - (2\gamma)\phi\left(\gamma(\rho^* - q)\right)}{\left(1 - (2\gamma)\phi\left(\gamma(\rho^* - q)\right)\right)} < 0 \text{ if } \gamma < \sqrt{\frac{\pi}{2}}$$

The following figure presents the above two results with $p(\rho^*)$ being the proportion of ordinary customers shifting to the new technology. For $\lambda = 0.4$, $\bar{s} = 4$, $\alpha = 300$, $\beta = 100$, $\theta \in [0,1]$.

P(ρ*) for $\lambda = 0.4$
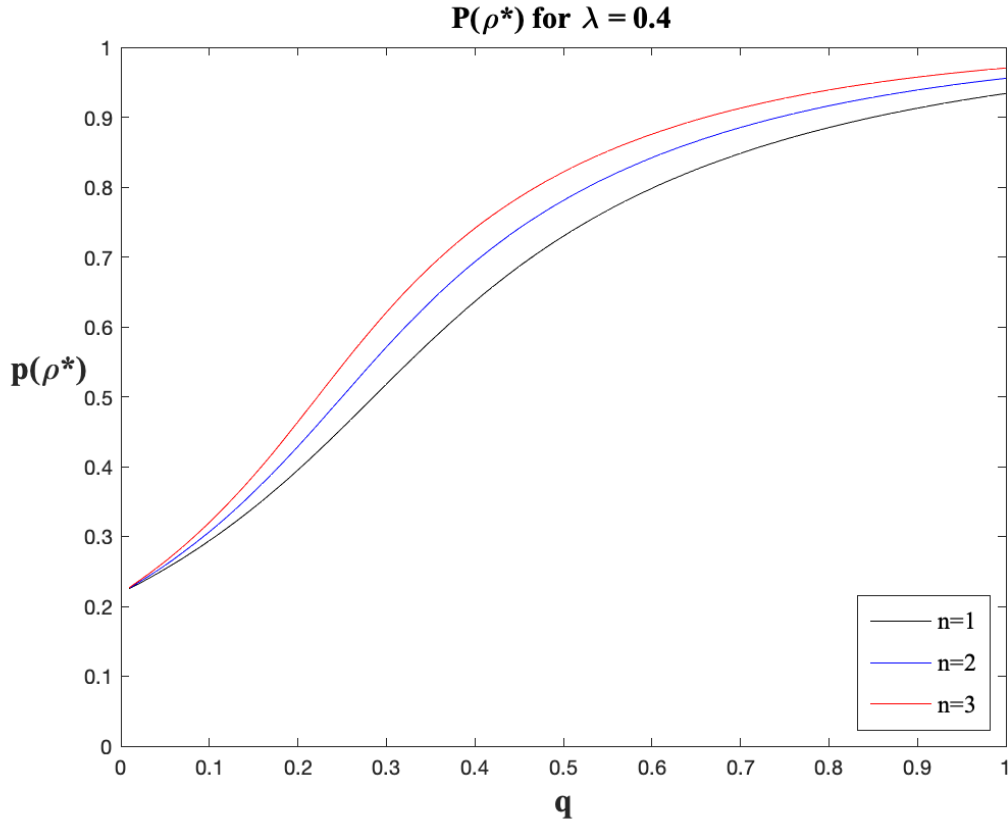
1.3 The merger game

To further simplify notation in what follows, we will assume that the quality of the entrant is always weakly higher (that is, $\underline{\theta} = 0$), so that if the merger takes place, the entrant's technology will be espoused.

By merging, the two platforms will generate over the n periods together

$$W^T = [\theta(\lambda+1) + (\lambda+1)1]n$$

in total welfare – the first term is the quality increment of the entrant, which is now enjoyed by all, and the second is the network externality enjoyed by ordinary customers, which is maximized because all customers are on the same platform. The per-period welfare within square brackets is multiplied by the number of periods to get total welfare. It can be rewritten as $[(\lambda+1)(\theta+1)]n$.

If the bargaining game breaks down, the surplus produced by the entrant E is given by

$$W^E(p^M, q) = [\theta(\lambda\frac{(1+m)q}{\overline{s}} + p^M) + (\lambda\frac{(1+m)q}{\overline{s}} + p^M)p^M]n = [(\lambda\frac{(1+m)q}{\overline{s}} + p^M)(\theta + p^M)]n$$

where p^M is the proportion of ordinary customers switching. Note that the proportion of ordinary customers switching is based on the techies' assumption that the merger would have taken place (i.e., that $m = 0$). This is appropriate since we are considering the out-of-equilibrium possibility that a merger, which was anticipated, does not take place.

The surplus produced by the incumbent is given by network externality enjoyed by the ordinary "remainers", which is

$$W^I(p^M, q) = [((\lambda+1) - \lambda\frac{(1+m)q}{\overline{s}} - p^M)(1 - p^M)]n,$$

Since $2q \leq \overline{s}$ and $p^M \leq 1$, then it is easy to see that $W^T \geq W^E + W^I$, so the merger is always ex-post efficient. This is not surprising since we have assumed bringing all the customers under the same platform will maximize the number of people enjoying the superior technology and the network externalities.[7]

Therefore, if mergers are not restricted by the antitrust authorities, a merger will always take place because it is efficient. The only question is at what price the transaction will take

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[7] Of course, if the incumbent's technology were superior, the incumbent would want to use its own technology, but would still make an offer to the entrant, so as to benefit from the network externalities associated with its customers. Mergers are always efficient, regardless of who has the technological advantage.

place. To discuss the price, we need to determine the profitability of the incumbent and the entrant, under the various scenarios. This is complicated by the fact that these are two-sided platforms, which charge zero on the consumer side of the market and make profits only on the advertising side. Since advertising generates negative utility to customers, the amount of a platform's advertising is limited by the consumer surplus the platform generates. Thus, we assume that by advertising a platform can extract in profits all the surplus it generates on the consumer side. In such a case, the price an entrant will pay in a merger is given by a bargaining game where we assume she can fully appropriate the surplus she generates under alternative scenarios.

If a merger takes place, we assume that with probability μ the incumbent makes a take-it-or-leave-it offer to the entrant. With probability $1-\mu$, it is the other way around. Thus, the entrant's payoff in case of merger is

$$\Pi^E(p^M,q) = \mu W^E(p^M,q) + (1-\mu)[W^T - W^I(p^M,q)]$$

In case a merger is prohibited by the antitrust, the payoff of the entrant is given by

$$\Pi^E(p^{NM},q) = W^E(p^{NM},q) = [\theta(\lambda\frac{(1+n)q}{\overline{s}}+p^{NM})+(\lambda\frac{(1+n)q}{\overline{s}}+p^{NM})p^{NM}]n.$$

Note that $W^E(p^{NM},q) \geq W^E(p^M,q)$ because $n \geq 1$ and $p^{NM} > p^M$ because of Corollary 1 – given the longer horizon m that switching techies have when mergers are not permitted, more will switch for any given q, lowering the threshold for ordinary customers to switch, and enhancing the measure of ordinary customers that switch to the entrant. Hence, if the entrant's bargaining power is zero, her payoff is larger when mergers are prohibited, even if the prohibition on mergers leads to firms not fully exploiting the network externalities and the technological gains.

Intuitively, if mergers are prohibited an entrant will attract a greater customer base for two reasons. First, in period 1, anticipating a longer period over which they will enjoy the quality differential, a greater set of techies will switch. Second, the greater number of techies will generate a greater network externality which will attract an even greater number of ordinary customers. Since she attracts more customers when mergers are prohibited, a new entrant will generate more surplus by itself under this scenario than in the scenario where the merger is anticipated to occur.

More generally, if her bargaining power is small, the entrant's payoff will be driven mostly by her outside option. Since we just showed that her outside option is bigger when mergers are prohibited, the entrant's payoff will be bigger when mergers are prohibited.

In practice, it is very difficult to prohibit mergers entirely. At best, a regulator can impose a very strict pre-merger notification rule and adopt a very careful review process. Such rules, however, might have the effect of making the acquisition more difficult, not eliminating it. Nevertheless, this intervention can still be useful. For our effect to work we do not need an absolute prohibition, but just some uncertainty on the final outcome. With sufficient uncertainty on when and whether a merger will take place, the techies will be prompted to switch, increasing the value of potential entrants.

1.4 Ex Ante Investment

Thus far, we have assumed that the technological improvement θ was manna from heaven. More realistically, this improvement is the result of some ex-ante investment made by the potential entrant. Let's assume that the potential entrant will face a cost C^E of R&D, drawn from a distribution. On paying this cost, she can draw a technology of quality θ from a distribution. Before she decides whether to enter, E will compare her expected profit with her known cost of R&D and enter if and only if $E_\theta[\Pi^E(\theta)] > C^E$. Prohibiting acquisitions by incumbent platforms can have the effect of increasing the expected profit of new entrants for any θ (for example, if $\mu \to 1$ in the merger negotiations, so that incumbents have tremendous bargaining power). This will increase the range of C^E that are viable, and increase the probability of investment in R&D and thus entry.

Notice that this result will hold even when prohibiting acquisitions is socially inefficient because of the ex post inefficiencies this policy generates. Thus, finding empirically that acquisitions lead to lower entry does not automatically imply that prohibiting acquisitions is the right policy. Nevertheless, our intent was to determine circumstances under which something as seemingly beneficial to the acquired as an acquisition offer could actually deter entry.

1.5. Determinants of Bargaining Power

Our theory implies that events that indicate the anti-trust authorities are more lenient in permitting platform acquisitions could potentially reduce entry in areas that are closely related – since observers will conclude that the anti-trust authorities will be similarly lenient in the case of the entrant. Of course, the theory suggests this is most likely when the incumbent has tremendous bargaining power. Before we turn to the data, let us discuss what might determine the incumbent's bargaining power, which we set in the model to a generic μ.

Notice that within our model a lower μ will always improve efficiency, since it will not affect decisions ex post, but it will increase investments and entry ex ante. This might not be true in a general model, where the incumbent also invests in innovation. Furthermore, any incumbent is a former start-up, thus the model should not be taken literally as suggesting minimizing μ is optimal. This said, there are several reasons to believe that μ is rather large in practice.

First, in a standard Rubinstein (1982) game, bargaining power μ is inversely related to the degree of impatience or the discount rate. The cost of capital of an incumbent – having undertaken a successful and often lucrative IPO, and enjoying a high stock price -- is much smaller than the cost of capital of an entrant. This difference alone could explain why μ might be close to 1.

Another important factor in determining the degree of impatience is the threat of replication. If the incumbent is allowed to copy the new entrant's innovation, the longer the period over which bargaining takes place, the higher the risk of replication. This increases E's impatience and thus I's bargaining power.

In many real world situations, negotiations take place under the veiled (and sometimes not so veiled) threat by the incumbent to drive the entrant out of business with aggressive behavior if she does not sell out. The incumbent's threat is maximized when it can easily replicate the technological features of the new entrant (see above). But even without this possibility, there are many ways in which an incumbent can make the new entrant's life difficult: from slashing prices on the revenue side of the platform to use its lobbying power. Most (if not all) these behaviors could be deterred by an active antitrust authority, but the recent historical record on this front has

been quite weak.[8] The awareness of this historical record can only increase the incumbent's bargaining power.

Last but not least, in the presence of network externalities, markets tend to be winner-take-all. Thus, the risk for any participant is not to be worth less: it is to be worth zero. Entrants are less suited to bear this risk, since they tend to have a more concentrated ownership structure than established incumbents whose shareholders are better diversified. This comparative disadvantage in bearing the risk of failure further weakens the entrant's bargaining power vis-à-vis the incumbent.

1.6. Negative Prices

One important assumption in our analysis is that prices for platform services are non-negative. Traditionally, this has been the case, but recently several companies have tried to find ways around this constraint. There are three major obstacles to pay people for using a platform. First, transactions costs can quickly mount, since each transaction tends to have a very low price. Second, there is the risk of abuse: arbitrageurs can design bots to benefit from payments intended for real people. Third, while in principle the platform with the superior technology should be able to offer the highest rebate, in practice liquidity constraints severely restrict new entrants' ability to pay.

The internet browser Brave has launched a reward system to pay customers for using its product and watching its ads.[9] To get around the afore-mentioned problems, Brave chose to pay users with its own bitcoin-style cryptocurrency called Basic Attention Tokens or BAT. BATs are utility tokens that are not convertible into dollars, but can be used to buy ads from Brave at a pre-determinate price. The idea is that their value will increase with the use of the browser. If – in addition—these tokens are traded, their values can signal to unsophisticated customers the value of the new technology. Indeed, Li and Mann (2019) have shown that token offerings can help resolve coordination problems.

A system of token-based payment can help mitigate the problems highlighted in this paper. We say "mitigate" since such tokens offered to techies can help them internalize the network externalities later faced by ordinary customers, giving them an added incentive to switch

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[8] See, for example, the battle between Quidsi and Amazon detailed in Khan (2017) and Stone (2013).
[9] https://www.wired.com/story/brave-browser-will-pay-surf-web/.

when the entrant technology is superior. However, the underlying effects of switching costs and the horizon-reducing effects of mergers will not be eliminated.

1.7. Internalizing the externality

A more effective alternative to paying customers is to subsidize techies to switch to the new platform, since they have a multiplicative effect on the number of customers who will eventually switch. In today's world these techies are called "influencers" and are indeed paid to induce people to switch. If it is known that switchers are paid, then the type of inference regular customers make when they observe a techie switching is very different from the one assumed in our model. Nevertheless, to the extent their action does signal some information, paying for influencers makes sense.

While the possibility of paying for influencers might reduce the frequency with which superior entrants fail to overcome incumbents, it does not eliminate (in fact, it might exacerbate) the ex-ante suboptimal incentives to invest in creating improvements for platforms. In fact, the influencers are capturing part of a rent they did not help create, thereby reducing the return to the entrant doing the actual investing.

1.8. Substitute and Complements

We have cast our model in terms of substitutes: an incumbent platform threatened by an alternative new platform. Yet, some of the major acquisitions done by Google are complements: take for instance the acquisition of Doubleclick, a company that displays and tracks banner ads across a network of websites. Our model can easily be restated in terms of the entrance of complements to the incumbent platform.

Assume the complement company (Doubleclick) provides an essential service that makes the platform (Google) more attractive to users (in this case, firms). Assume that the platform already provides that service, but in a less effective way. If the platform is prohibited from acquiring the complement, users will switch for the particular complementary function to the complement producer, enhancing its value from the network externalities (in this case, the additional information it gets from diverse users to improve its product). If the platform can acquire the complement, potential switchers may be reluctant to incur switching costs, continuing to use the lower quality service provided by the platform until the acquisition takes

place. Given that the complement is thus also lower quality as a stand-alone entity (having attracted fewer switchers and having less data to use in product development), its acquisition price will be lower than if mergers had been prohibited. The rest of the implications follow.

There is an additional issue with complements. If there is only one monopoly incumbent platform that can possibly acquire the complement, then once the acquisition takes place, the remaining budding entrant firms providing that complement have no possibility of being acquired and may even have no customers for their product. It is not surprising that investment in them will fall precipitously. Of course, if the platform market is oligopolistic, it gets a little more complicated. Once a complement is acquired by a platform, there is a smaller market available for the remaining complements – to either sell their services to, or to sell themselves to. This should depress the acquisition price and investment in such firms. There is another effect, though. If there are only a few such complements available, the remaining platforms may bid vigorously in order to compete with the services provided by the platform that has already bought one. The net effect on acquisition prices and investment is ambiguous.

There is a final possibility – one where Doubleclick is not valuable as a stand-alone company, but only in combination with one of the existing digital platforms. Let's assume that there is an incumbent platform (Google) and a challenger (Bing). The price that Doubleclick can obtain from Google depends upon Bing's bid for Doubleclick. But Bing's bid for Doubleclick depends upon the number of customers who are willing to switch to Bing. If Google's customers anticipate that the acquisition of Doubleclick will take place and that the combination Google-Doubleclick will be superior, they have little incentive to switch to Bing, even if Bing (before Google's acquisition of Doubleclick) was technological superior. This resistance to switching will reduce not only the value of Bing, but also the price that Bing is able to offer to Doubleclick and thus, ultimately, the price Google will have to pay to acquire Doubleclick.

By contrast, if there is uncertainty whether the Google-Doubleclick merger would be allowed, more Google customers will be willing to try and switch to Bing, increasing the amount of value Bing creates by buying Doubleclick. As a result, Bing would be able to bid higher for Doubleclick, increasing the price at which Doubleclick will be bought. In this case, network externalities and switching costs do not depress the value of the platform itself, but the value of the complement to the platforms, reducing their incentives to invest.

2. The Data

The model presented above explains why banning mergers may positively affect innovation and investment. Ideally, we would like to study the impact on start-up investments of a decision by antitrust authorities to strike down a big acquisition by a major digital platform. Unfortunately, we have not observed any such decision yet. Therefore, we need a different strategy.

Big companies are unlikely to decide a major acquisition without having a fairly high degree of confidence that such an acquisition will be accepted. Thus, we will consider the announcements of major acquisitions as a signal that the US Federal Trade Commission and the Department of Justice will let these, and similar, acquisitions go through. We then analyze the impact on investment decisions by related early stage companies.

We focus on the major acquisitions of software companies conducted by Facebook and Google from the beginning of 2006 to the end of 2018. We focus on Facebook and Google because they are two prominent incumbent two-sided platforms that charge a zero monetary price on one side of the market, as described in the model. We restrict attention to their major acquisitions because we think that only those acquisitions convey a strong signal of likely future antitrust attitude towards acquisitions. Finally, we focus on software companies because we are looking for start-ups that can develop into potential competitors of the incumbent platforms.

The source of our data is *Pitchbook.* We select all the software companies purchased by Facebook and Google for more than $500M. There are 9 acquisitions that satisfies these criteria: 7 by Google and 2 by Facebook. We list them in Table 1.

With traditional technologies it is simple to determine whether a product or service is a complement or a substitute: a match is a substitute to a lighter because the demand for matches goes up when you tax lighters. It is a complement to cigarettes because the demand for matches goes down when you tax cigarettes. With multisided digital platforms, it is more complicated, because the definition depends upon which side of the platform one looks at. It is easy to classify both WhatsApp and Instagram as substitutes of Facebook, but what about Youtube and Google? From a consumer perspective, Google search is a complement to Youtube, because customers need to search for videos before they watch them. Yet, on the advertising side of the business, Youtube is a substitute because it can provide clients with an alternative way to microtarget ads.

Therefore, we define as a substitute a product or service that can replace either the customer base or the ad base of a platform, leading to a potential substitution of the existing

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platform with a new one. Using this definition, not all the acquisitions we have are substitutes. For example, AdMob (a company that offered advertising solutions for several mobile platforms) and Doubleclick (a company that displayed and tracked banner ads across a network of websites) are complements, since they enhance the ad experience of existing platforms, but – by themselves—cannot replace any of the platforms. The same can be said for Postini and Apigee. Postini was an e-mail, Web security, and archiving service, very useful to enhance the functioning of Gmail, but not able – by itself—to replace email. Apigee was an API management and predictive analytics software provider, again very useful to the Google experience but not a potential substitute for any business of Google.

The distinction between complement and substitute is further complicated by the multi-market nature of these platforms, especially Google. Google does not only offer search services, but also email services (Gmail), navigation services (Google Maps), and traveling services (Google Trips). More importantly, these services do not operate as independent units of a conglomerate, but they are integrated (at least from a data collection point of view) to offer advertisers the best possible experience. Thus, it is easy to classify Waze, a navigation software, as a substitute, because it directly competes with Google Maps. For the same reason, we should classify "ITA software" (an airfare search and pricing system) as a substitute. While it is difficult to imagine that in 2010 ITA software could replace Google as an overall search engine, it was competing head-to-head with Google in an important segment of the search market, i.e., travelling. Bearing all these caveats in mind, the last column of Table 1 summarizes our (no doubt, subjective) classification of the major acquisitions of the two digital platforms into substitutes and complements.

Pitchbook classifies venture capital financing according to two criteria: 1) Financing Stage, which classifies the stage of development at which a firm is financed (Accelerator/Incubator, Seed, Angel, Early Stage, Later Stage); 2) Financing Rounds, which track the sequential order of external financing. For most of our analysis we focus on early stages (from Accelerator-Incubator to Early Stage). To focus on new entry, we will occasionally limit our attention to the first round of financing, which we will term *new deals*.

For all nine acquisitions, we collect the *total dollar amount* invested by venture capital companies in start-up companies operating in the same "space" as the company acquired and the *number of VC deals* funded. We determine whether a start-up belongs to the same space as the

acquired company (and is thus "treated") based on two metrics. The first metric relies on a text-based measure of similarity produced by *Pitchbook.* Similar to Hoberg and Phillips (2016), *Pitchbook* applies a machine-learning algorithm to companies' business descriptions to measure their degree of similarity.[10] In Table 2 and 5, we experiment with different thresholds of similarity between 75% and 90%.

The second measure classifies startup companies as "treated" if they belong to the same primary industry and operate in the same industry verticals as the acquired company. The primary industry, according to Pitchbook, is the industry subgroup in which the company primarily operates. The industry vertical is a specific element of the company which isn't accurately captured by industry subgroup. Verticals are useful in identifying companies that offer niche products. For example, WhatsApp belongs to the primary industry *Communication Software,* which is one of the sixteen subgroups in the industry group *Software*, which in turn is one of the six industry groups in the sector *Information Technology*. Further, WhatsApp belongs to the *mobile sector* vertical.

We collect data on similar startup companies (to the target) for each of 7 observation years for each acquisition – the 3 years before the acquisition year + the acquisition year + the 3 years after. As Table 2 shows, there is a trade-off between narrowing the definition of similarity and reducing the number of "treated" early stage companies. If we use a threshold of 85%, we lose 14% of the observations and one quarter of the remaining observations is based on a set of less than 5 companies. If we increase the limit to 90%, we lose almost a third of the sample and for half of the remaining ones we have at most four companies as a comparison set. By contrast, if we lower this threshold to 75%, the treated group consists of up to 480 companies, possibly increasing the noise. For this reason, we start with an initial threshold of 80% similarity. With this threshold, we have no treated company in only three observation years, which we drop from the sample.

Table 2 reports the summary statistics of the relative level of investments and number of deals using both measures of similar "treated" startups and normalizing by the early VC deals in the software industry. Table 2 also reports the summary statistics for new investment deals (first

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[10] https://techcrunch.com/2018/06/19/pitchbook-now-offers-users-suggested-companies-when-they-search/.

stage investments in the similar startups) and its sub-groups namely substitutes and complements.

3. Empirical Results

3.1 Main Results

In Figure 1, we plot the raw number of early venture capital deals and the dollar amount invested in early deals in the social media space. The number of deals peaks in 2014, the year of Facebook acquisition of WhatsApp, and the amount invested peaks shortly after, in 2016. While these pictures are broadly consistent with the idea that VC funds shy away from social media after the consolidation of the power of Facebook, they are certainly not conclusive. The decline over time can be driven by many other factors. To try to control for these other factors, in all the following analyses we will deflate all the numbers by the overall VC investment in the software sector during the same years.

In Figure 2a, we plot the normalized relative amount invested in treated companies, around an acquisition event. For each acquisition, we identify as "treated" the startups with an 80% Pitchbook similarity (defined in Section 2) as the company acquired. For each of the 63 observation years [= (3 years before+ acquisition year + 3 years after)*9 acquisitions], we sum the investment across treated startups. To adjust for cyclicality, this sum is deflated by the total investment made that year by venture capitalists in the software sector (defined by Pitchbook as belonging to the industry sector 'software'). This ratio is expressed in percentage terms, and termed relative investment. Since each acquisition has a different number of comparable "treated" startups, we normalize the seven annual observations of relative investment for each acquisition by the relative investment in the year of the acquisition. This normalized relative investment is therefore 1 in the year of the acquisition for all acquisitions. Then, we average these ratios across the nine events using event time, as is commonly done in event studies. As we can see from Figure 2a, the normalized relative level of investment drops over 40 percent in the three years following an acquisition.

As a comparison, we selected all software acquisitions (100% stake) other than those by Facebook or Google for more than 500M dollars between 2006 and 2016. There are 178 such

acquisitions for which we have data. Far from falling post acquisition, normalized relative investment in the software industry rises by over 40 percent.

In Figure 2b, we plot the normalized relative number of startup investments. While the normalized relative number of deals falls by over 20 percent in the 3 years following the Facebook/Google acquisitions, they are relatively flat for other software acquisitions. In what follows, we will substantiate these findings through regressions. The pre-trend decline in the relative number of deals is not surprising. In early stages, the VC investment rounds are more frequent (Gompers, 1995). As firms mature, rounds become less frequent: hence a decline in the raw number of deals. The pre-event decline, however, accelerates substantially after a Facebook/Google acquisition, as Figure2b shows, in contrast to the normal acquisition in the software industry.

In Table 3 we present similar results in regression format. The dummy variable post-acquisition equals to 1 in the three years after the acquisition. In columns 1- 2, the left hand side variable is the relative level of investment (without normalization), computed as described above. As column 1 in Panel A shows, the dummy variable post-acquisition has a negative and statistically significant coefficient. Relative investments drop by 0.97 percentage points after acquisition. Given the average is 2.1 (see Table 2 for Pitchbook similarity>80), this corresponds to a 46% drop in the three years after an acquisition. In column 2, we include a fixed effect for every acquisition – this has the same effect as the normalization we did in plotting Figure 2, since each acquisition has a different number of comparable startups. Thus, column 2 focuses on the time series variation of the sample of treated companies for each acquisition. The coefficient is of similar magnitude to the one estimated in column 1 but understandably more significant statistically.

Columns 3 and 4 of Table 3A analyze the relative number of acquisitions. After an acquisition the relative number of deals drops by 0.85 percentage points. Given that the sample average is 1.7 (see Table 2), this corresponds to a 50% drop. The estimated coefficient on the post-acquisition indicator is qualitatively similar if we include an acquisition fixed effect, but statistically more significant (column 4).

In Table 3 Panel B, we repeat the analysis with the industry-based measure of similarity. In column 1 we see that there is a drop in relative investments, of about 1 percentage point, although this drop is not statistically different from zero. Since the sample average is 2.5%, this

corresponds to a 36% drop. Introducing a fixed effect for each of the nine acquisitions (column 2) does not change the coefficient, but it makes it statistically different from zero at the 5% level.

In columns 3 and 4, the dependent variable is the relative number of deals. After an acquisition, it drops by 0.8 percentage points, equal to a 32% drop (column 3). The effect is similar if we include a fixed effect for each of the nine acquisitions, but once again of greater significance (column 4).

In sum, regardless of the measure of similarity used, we observe that companies similar to the ones acquired experienced a significant drop in investments and number of financing deals after the acquisition by Facebook or Google.

We could also re-estimate Table 3 for normalized measures (as in Figure 2). Once we normalize, the inclusion of fixed effects should have little influence on the magnitude or significance of the estimated post-acquisition coefficient. And indeed it does not, as Table 4 shows.

3.2 Similarity

In Table 5, we compare the effect of acquisitions on relative investments when we change the threshold of similarity in the Pitchbook measure. No matter what the threshold is, the estimated effect of an acquisition is negative and statistically significant, in spite of the decline number of observations. The magnitude of the coefficient drops as we go toward greater similarity, but so does the average of the relative investment in the sample (see Table 2). When we take this fact into consideration, the percentage decline increases in magnitude from -43% to -67%.

We can address another concern by sorting on similarity. An alternative explanation of these results is that most of the start-ups that are very similar to the one acquired by Google or Facebook were created with the hope of being acquired by Google or Facebook. Thus, when the two tech giants choose a specific target, the potential alternatives loose financing.[11] To address this concern further, we selected as a treated group a set of start-ups that are similar to the acquired ones, but not too similar. From a practical point of view, we look at investments and number of deals of start-ups that have a Pitchbook measure of similarity between 75% and 85%.

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[11] A more sinister explanation (more consistent with the one we propose) is that the acquisition-augmented Google or Facebook is an even more indomitable competitor for future entrants. Regardless, it is heartening for our model that the effects are large across a wide range of possible entrants.

The results in Table 6 are similar to the ones in Table 3. There is a quantitatively large drop in investments and deals after an acquisition.

Even if acquisitions deter new investments, a VC firms might find it optimal to continue financing its existing start-ups, because most of the investments is already sunk and suspending any additional financing might imply a total loss. Yet, the same logic does not apply for the totally new investments. For this reason, in Table 7 we repeat the analysis of Table 3, restricting our attention to first round investments only. As in Table 3, acquisitions have a negative and statistically significant impact on the amount invested in new start-ups and on the number of new start-ups financed.

3.3 Complements and Substitutes

In Table 8, we split the sample based on our classification of complements and substitutes (see Table 1). The pattern of results is similar in both subsamples. While the drop in relative investments seems similar for complements and substitutes, this is not true once we compare with pre-existing levels. As Table 2 shows, the average level of investments in substitutes before an acquisition is 0.5, thus there is a 76% drop, versus the 34% drop experienced by complements (which have a pre-acquisition level of 1.2).

3.4 Including all acquisitions

The post-acquisition decline in investments we documented in the previous tables may not be specific to acquisitions made by incumbent digital platforms like Google and Facebook, but common to all acquisitions. To check whether this is indeed the case in Table 9 we expand the sample to include all the acquisitions of software companies for more than 500M dollars that took place between 2006 and 2016.

Column 1 reports the same specification as in Table 3, where the dependent variable is the relative investment and as control variables we have a dummy for the post-acquisition period, a dummy if an acquisition is made by Google or Facebook, and an interaction between these two dummies.

Sectors targeted by Facebook and Google exhibit significant lower investments in general, suggesting Facebook and Google may crowd out investments even before they acquire. In addition, all segments of the software industry seem to experience a decline in investment

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after an acquisition. Yet, we are mostly interested in the coefficient of the interaction term. If the decline in investment is more pronounced when the acquisition is made by Facebook or Google we should observe a negative and significant coefficient of the interaction term. The coefficient is indeed negative and twice as large as the coefficient of the post-acquisition dummy alone, but understandably is not statistically significant. When we control for acquisition fixed effects (column 2), however, the coefficient becomes statistically different from zero at the 5% confidence level.

In columns 3 and 4 we repeat the same analysis with the number of deals as dependent variable. In both specifications the interaction term has a negative and statistically significant coefficient.

In sum, Table 9 reveals that the post-acquisition drop in investments is present even when the acquirer is different from Google or Facebook. Yet, the decline in investment is twice as large for Google-Facebook deals, and the decline in deals is almost 5 times larger than for an ordinary software acquisition, suggesting the problem is more severe.

4. Policy implications and Extensions

4.1 Anti-Trust Policy

It is not straightforward to go from our findings to policy. In our model, allowing incumbent platforms to acquire new entrants enhances ex-post efficiency, but may reduce the ex-ante incentives to innovate. Thus, the overall welfare implications of allowing mergers depend on the relative importance of ex-ante underinvestment vis-à-vis ex-post inefficiency.

A case-by-case approach will inevitably lead to the anti-trust authorities approving all acquisitions, because ex-post efficiency considerations would prevail (at that point the investments are sunk and in a case-by-case approach current decisions will not bind future ones). A blunt non-contingent rule (e.g., no large acquisitions by main incumbent platforms will be allowed) will provide greater predictability of outcomes, possibly stimulating greater innovation; but it can be very costly, because it prevents the industry from realizing ex post efficiencies. For this reason, it is preferable to consider other possibilities. The advantage of modeling the key frictions is that the model can suggest alternative fixes.

4.2 Interoperability

A crucial friction in our model is the cost of switching. In the model we assumed this cost to be an exogenous parameter. Yet, companies can affect this switching cost and they generally prefer to increase it, so as to increase their market power. The regulatory authorities can affect switching costs too. A simple way to reduce switching costs is to mandate a common standard. For example, all plugs in America are the same, making it easier to connect our appliances. In the same way, the internet access protocols are standard, allowing a world wide web.

In a similar way, we assume the existence of network externalities associated with belonging to specific networks. Such network externalities, however, are not just an inevitable consequence of a technology, but a combination of technology and standards. In the early phone industry, there were enormous network externalities because one could only call people on the same network. When the U.S. government mandated interoperability among the various phone-service providers, network externalities associated with specific networks disappeared. The same can be done for social media. If the government mandates a common Application Program Interface (API), it is easier for intermediaries to connect customers participating on different social media. So, both the switching costs and the network externalities are greatly reduced.[12]

Recall that a key friction in our model is the presence of network externalities associated with each competitor's network. When everyone can get access to the externalities associated with the whole network, there is no distortion in the incentive to innovate because the better product will always prevail. Thus, by forcing interoperability, the regulatory authorities can restore the proper incentive to innovate.

4.3. Data Ownership

We have assumed no constraints on the entrant's ability to innovate. In the digital world, past customer-generated data are crucial to fine tune new products offered to consumers. Thus, incumbent-collected data on the customer represents an important barrier to entry for newcomers – effectively lowers the distribution of θ for any investment C^E. The greater access to customer

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[12] Alternatively, customer experience across platforms could be standardized, minimizing switching costs. Techies, however, may want to go beyond the ordinary customer experience into the details of every feature. These may be harder to standardize. Furthermore, the incumbent may gain an advantage here, since she participates in setting the standards, and they will be best suited to the features she has.

data entrants have, the more they can fine-tune their products, leveling the playing field with the incumbent. Thus, default allocation of data ownership is crucial in spurring competition and innovation. Rules that allow incumbent platforms free use of their accumulated data make it easier for incumbent to exploit their network externalities in different lines of business. If a platform, for example, can freely use its customer information to market a new cryptocurrency, it can easily gain a head start vis-à-vis any other cryptocurrency. Thus, the incentives to innovate in any area where an existing platform can expand are curtailed by the possibility that the platform might enter with a data advantage.

The new European data protection rule – also known as GDPR – limits the use of these data by incumbents, unless they have asked explicit authorization from the customers. In so doing, it reduces the incumbent's advantage somewhat, promoting innovation. Of course, it also means that entrants will have to ask each customer for permission to use their data, increasing their costs of fine-tuning also. There have also been proposals to allow customers to own their data, and sell it to whomsoever they desire (see Lanier (2013), Posner and Weyl (2018)). This would level the playing field, provided data collectors are compensated for their cost of collection, and data intermediaries arise to facilitate storage and sales.

4.4. Patent Protection

In a similar vein, it follows that the more an incumbent can freely copy the technological innovations of new entrants, the worse the incentives of early adopters to switch to a new entrant will be, and thus the lower the incentives to innovate will be. This feature is not unique to our model. Even in a neoclassical model of competitive innovation, lack of protection of innovation will curtail innovation incentives. In our model, however, the effect is much stronger. In the traditional duopoly setting, if the incumbent perfectly imitates the innovation of the new entrant and it sells it at the same price, the new entrant still can sell its product. In our model, if the incumbent perfectly imitates the new features of the entrant, the new entrant will not be able to attract customers because the incumbent's network externalities will dominate. Thus, in the absence of any patent protection, the incentives to enter with a superior product will be severely curtailed.

Note, however, that a very strong patent protection system can be a double-edged sword, because it protects incumbents' property rights too, possibly creating an insurmountable

advantage over potential entrants (see Bryan and Hovenkamp (2020)). To properly derive the optimal degree of patent protection, we would need to model the incumbent's incentives to innovate. This is outside the scope of this paper.

4.5. Keeping out Foreign Incumbents

The possibly adverse effects of incumbent platforms acquisition on innovation and entry may perhaps also be gleaned from the history of digital platforms in the United States, China, and the EU. The EU, which has a market as large as the United States, did not produce its own home-grown giants. By contrast, China, which has blocked the acquisition and entry of foreign platforms, has created an ecosystem of platforms (from Ali Baba to Baidu and Tencent) that rivals those in the United States. A possible explanation, consistent with our model, is that EU entrants had to contend from the beginning with US incumbents, who built extensive networks in Europe early on. By contrast, Chinese entrants did not have the same problem.

In the future, India might provide an interesting testing ground. Initially, India had allowed relatively free entry to foreign-owned platforms. Recently, however, it has introduced a new set of rules hamstringing the dominant incumbent foreign-owned market places, Amazon and Flipkart (owned by Walmart), with the intent of creating more incentives for domestic entrants. Only time will tell if this approach is successful in growing domestic champions.

The above argument is nothing more than a variant of the standard argument for protection of "infant" industries proposed by Alexander Hamilton and developed by Friedrich List. As in Section 4.4, network externalities just make the case much stronger. In addition, our model suggests that the "infant" industry protection argument can be used not just in new industries, but also in developed ones, like the software industry in the United States. Of course, all the traditional caveats associated with the infant industry argument still pertain here.

5. Conclusions

Venture capitalists talk about a "kill zone" created by acquisitions, such as those by Facebook and Google, in the start-up space. This idea seems at odds not only with standard textbook economics, but with logic itself. Why should the prospect of being acquired at hefty multiples *discourage* new entry?

In this paper we construct a simple model that rationalizes this result. In the presence of network externalities, early adopters generate an important externality: they facilitate the adoption by less sophisticated customers, helping the market converge to the platform with the superior technology. These early adopters, however, face significant switching costs, thus they will switch only if the benefit of switching is reasonable large. This benefit is given by the product of the technological difference and the time this difference will persist. Since a merger immediately transmits the superior technology to everybody, it reduces the payoff to early adoption. The prospect of mergers then reduces switching, makes it harder for entrants to acquire customers and offer network externalities for any given technological superiority, and thus reduces the price at which they can be acquired. This then reduces their incentive to innovate.

We test this prediction using data on investment in startups. We show that VCs significantly reduce the number of deals and the amount of money they invest in markets near one where Facebook and Google have made a large acquisition, after the two giant digital platforms have made those acquisitions. While an outright prohibition of acquisitions may reduce welfare, the model provides alternative welfare-improving forms of intervention.

The most important message, though, is a simple one: it is dangerous to apply twentieth century economic intuitions to twenty first century economic problems. Our paper suggests one reason why.

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Figure 1: VC Investment and Deals in the Social Media Space

Figure 1a plots the number of early-stage start-ups financed by a venture capitalist in the social media space. Figure 1b plots the actual dollar amount of funding going to early-stage financings of start-ups in the social media space. Source: Pitchbook.

(a) Number of Deals
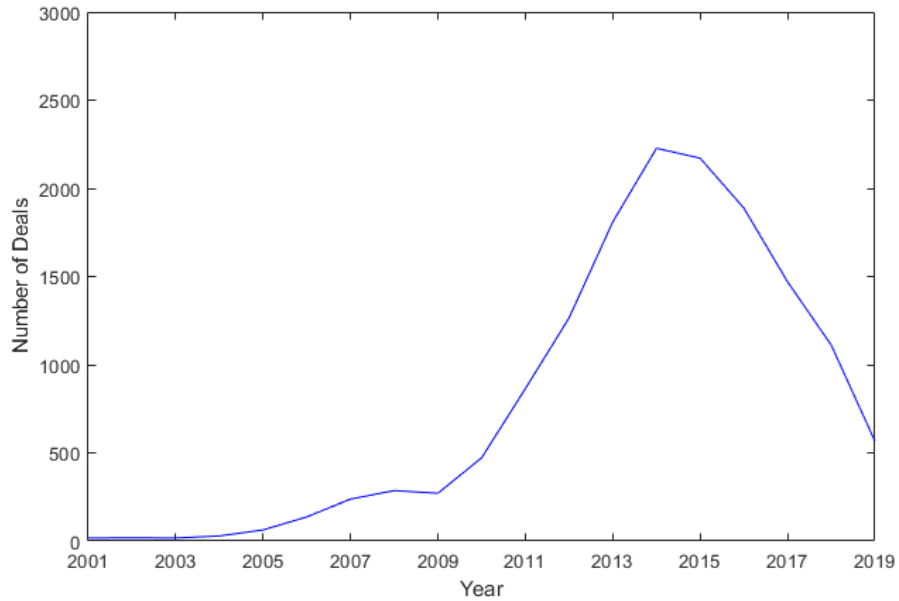
(b) Investment: Dollar amount financed (in million $)

Figure 2: Effect of Acquisitions on Amount of Investments and Number of Deals

In Figure 2a, the average normalized relative VC investment in early stage companies similar to the one acquired is plotted in event time both for Facebook/Google acquisitions and for other acquisitions in the software industry between 2006 and 2016. To adjust for cyclicality, the amount of investments in comparable "treated" companies is divided by all VC investments in early deals in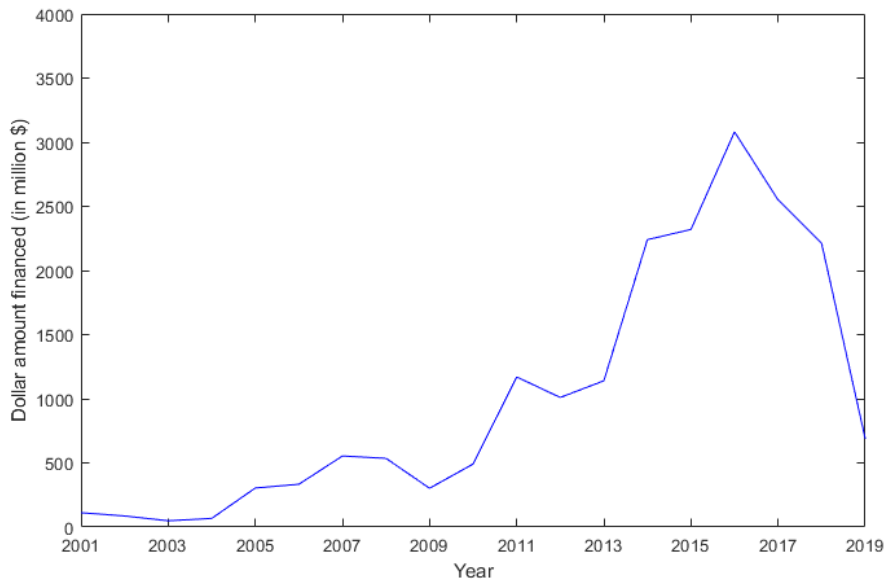 the software industry made in the same year. This ratio, relative investment, is then normalized by the relative investment in the year of the acquisition, so that the normalized relative investment is one in the year of the acquisition for each acquisition. The normalized relative investment in each acquisition-year is then averaged across the nine Facebook/Google acquisitions. As a comparison, we repeat this plot for all other acquisitions in the software industry. In Figure 2b, the average normalized relative number of VC investments in early stage companies is similarly computed for the Facebook/Google acquisitions as well as the other acquisitions in the software industry. Source: Pitchbook

(a) Normalized relative investment before and after an acquisition
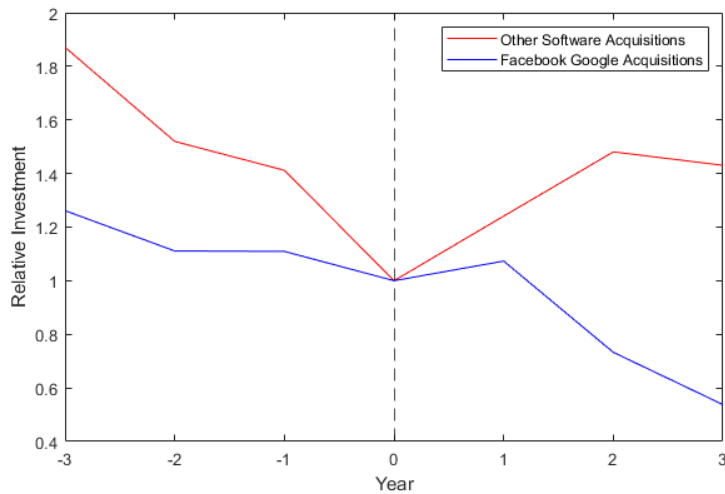
(b) Normalized relative number of deals before and after an acquisition

38
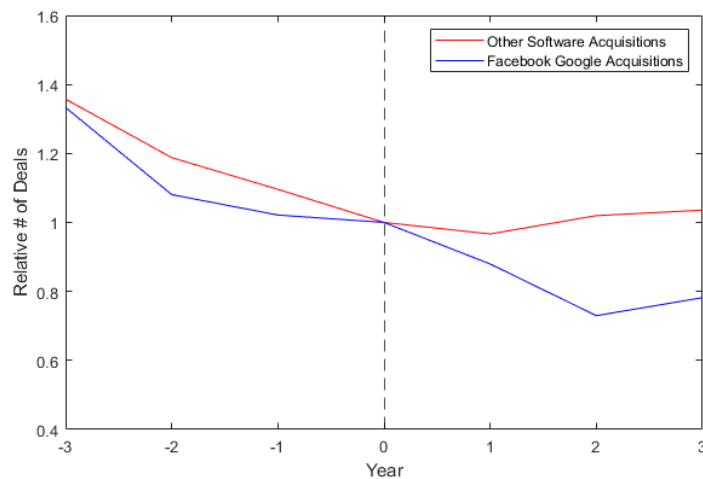
Table 1. Acquisitions Considered

The list of all software companies acquired by Facebook or Google for more than $ 500 million between the beginning of 2006 and the end of 2018 is listed. Price paid is the total amount paid in millions of dollars to acquire the company. Software Sector presents the primary industry of the target company in the software sector. Each target company is categorized as either a substitute or a complement based on its complementarity with respect to the acquirer. Source: Pitchbook

Year	Acquirer	Target	Price paid ($M)	Software Sector	Complementarity
2006	Google	Youtube	1,650	Multimedia and Design	Substitute
2007	Google	DoubleClick	3,100	Internet	Complement
2009	Google	AdMob	750	Vertical Market	Complement
2009	Google	Postini	625	Network Management	Complement
2011	Google	ITA Software	676	Vertical Market	Substitute
2012	Facebook	Instagram	1,000	Social Platform	Substitute
2013	Google	Waze	966	Communication	Substitute
2014	Facebook	WhatsApp	19,000	Communication	Substitute
2016	Google	Apigee	625	Development Applications	Complement

Table 2. Summary Statistics

For each of the 9 acquisitions listed in Table 1, we collect data for a 7 year-window centered on the acquisition year. The investment relative to VC investments is the ratio of the amount of VC investments in companies similar to the one acquired divided by the amount of VC investments in the software industry in the same year. This ratio is expressed in percentage terms. The number of deals relative to total VC deals is the ratio of VC deals in companies similar to the one acquired divided by the number of VC deals in the software industry in the same year. This ratio is expressed in percentage terms. Number of comparison companies is the number of similar startup companies for each acquisition. In (a), we consider similar companies to have the same industry sector and vertical as the acquired company. In (b), (c), (d), and (e) we consider companies as similar if they have a Pitchbook measure of similarity above 75%, 80%, 85%, and 90% respectively. In (f) we consider companies as similar if they have a measure of similarity between 75% and 85%. In (g) we look only at the first round of financing. In (h) and (i) we divide the acquisitions into complements and substitutes (see Table 1).

Variable	Mean	St Dev	Min	25th	50th	75th	Max	Obs
(a) Similarity based on sector and vertical								
Investment relative to total VC investments	2.9	2.8	0.1	0.6	2.2	4.2	12.9	63
Number of deals relative to total VC deals	2.5	2.0	0.1	0.7	2.2	3.7	7.8	63
Number of comparison companies	93.1	119.7	2.0	19.0	36.0	131.0	480.0	63
(b) Similarity based on Pitchbook index >75								
Investment relative to total VC investments	4.5	4.2	0.0	1.9	2.9	7.2	20.6	63
Number of deals relative to total VC deals	4.1	3.8	0.0	1.8	2.4	6.7	17.7	63
Number of comparison companies	153.7	169.2	1.0	36.0	98.0	213.0	746.0	63
(c) Similarity based on Pitchbook index >80								
Investment relative to total VC investments	2.1	1.9	0.0	0.7	1.9	2.8	10.5	60
Number of deals relative to total VC deals	1.7	1.5	0.0	0.6	1.5	2.3	8.4	60
Number of comparison companies	72.0	79.8	1.0	19.0	34.0	84.5	282.0	60
(d) Similarity based on Pitchbook index >85								
Investment relative to total VC investments	0.9	0.8	0.0	0.3	0.8	1.3	4.4	54
Number of deals relative to total VC deals	0.6	0.5	0.0	0.2	0.5	0.8	2.6	54
Number of comparison companies	28.2	37.4	1.0	5.0	10.5	35.0	121.0	54
(e) Similarity based on Pitchbook index >90								
Investment relative to total VC investments	0.6	0.8	0.0	0.1	0.3	0.7	4.1	43
Number of deals relative to total VC deals	0.2	0.1	0.0	0.1	0.2	0.3	0.5	43
Number of comparison companies	10.5	12.0	1.0	1.0	4.0	18.0	41.0	43
(f) Similarity based on Pitchbook index >75 & <85								
Investment relative to total VC investments	4.3	4.0	0.0	1.5	2.5	6.6	18.1	54
Number of deals relative to total VC deals	4.1	3.5	0.2	1.5	2.3	7.0	15.2	54
Number of comparison companies	28.2	37.4	1.0	5.0	10.5	35.0	121.0	54
(g) New Deals								
Investment relative to total VC investments	0.8	0.7	0.0	0.2	0.8	1.1	4.2	58
Number of deals relative to total VC deals	1.2	0.9	0.0	0.4	1.1	1.5	4.2	58
Number of comparison companies	56.9	65.2	1.0	11.0	26.0	69.0	235.0	58
(h) Substitutes								
Investment relative to total VC investments	0.5	0.4	0.0	0.1	0.4	0.9	1.5	30
Number of deals relative to total VC deals	0.9	0.9	0.0	0.3	0.5	1.3	3.0	30
Number of comparison companies	60.8	72.4	1.0	5.0	32.0	69.0	235.0	30
(i) Complements								
Investment relative to total VC investments	1.2	0.8	0.1	0.8	1.0	1.5	4.2	28
Number of deals relative to total VC deals	1.5	0.9	0.2	0.9	1.4	1.7	4.2	28
Number of comparison companies	52.6	57.4	10.0	16.0	22.0	81.5	167.0	28

Table 3. Post-Acquisition Decline in Investments and Deals

The dependent variable in the columns (1) and (2) is the amount of VC investments in startup companies similar to the acquired one divided by all VC investments in early-stage deals in the software industry. The dependent variable in the columns (3) and (4) is the number of VC deals in companies similar to the acquired one divided by all VC early-stage deals in the software industry. In Panel A, a start-up is considered similar to the acquired company if it has a Pitchbook measure of similarity with the acquired company above 80%. In Panel B, a start-up is considered similar if it shares the same industry sector and vertical. Post acquisition is an indicator variable that is equal to 1 in the 3 years after the acquisition. t-statistics are reported in parentheses, * $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

	Relative Investment		Relative # of Deals	
	(1)	(2)	(3)	(4)
Panel A: Pitchbook-based measure of similarity				
Post acquisition indicator	-0.967**	-0.927***	-0.845**	-0.813***
	(-2.22)	(-3.06)	(-2.44)	(-3.96)
Constant	2.521***	2.504***	2.088***	2.074***
	(6.61)	(11.04)	(6.76)	(13.81)
Acquisition Fixed Effects	No	Yes	No	Yes
Number of observations	60	60	60	60
Adjusted R^2	0.067	0.646	0.079	0.753
Panel B: Industry-based measure of similarity				
Post acquisition indicator	-1.044	-1.044**	-0.812*	-0.812***
	(-1.60)	(-2.58)	(-1.69)	(-3.07)
Constant	3.397***	3.397***	2.830***	2.830***
	(6.35)	(11.84)	(7.39)	(15.75)
Acquisition Fixed Effects	No	Yes	No	Yes
Number of observations	63	63	63	63
Adjusted R^2	0.035	0.706	0.040	0.770

Table 4. Post-Acquisition Decline in Normalized Investments and Deals

The dependent variable in the columns (1) and (2) is the amount of VC investments in startup companies similar to the acquired one divided by all VC investments in early-stage deals in the software industry (which is the relative investment) and further normalized by the relative investment in the year of the acquisition. The dependent variable in the columns (3) and (4) is the number of VC deals in companies similar to the acquired one divided by all VC early-stage deals in the software industry (relative number) and further normalized by the relative number in the year of the acquisition. In Panel A, a start-up is considered similar to the acquired company if it has a Pitchbook measure of similarity with the acquired company above 80%. In Panel B, a start-up is considered similar if it shares the same industry sector and vertical. Post acquisition is an indicator variable that is equal to 1 in the 3 years after the acquisition. t-statistics are reported in parentheses, * $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

| | Relative Investment (Normalized) | | Relative # of Deals (Normalized) | |
	(1)	(2)	(3)	(4)
Panel A: Pitchbook-based measure of similarity				
Post acquisition indicator	-0.318**	-0.314**	-0.292***	-0.305***
	(-2.20)	(-2.54)	(-2.73)	(-3.33)
Constant	1.088***	1.087***	1.086***	1.092***
	(9.29)	(12.36)	(14.15)	(17.26)
Acquisition Fixed Effects	No	Yes	No	Yes
Number of observations	60	60	60	60
Adjusted R^2	0.069	0.457	0.110	0.447
Panel B: Industry-based measure of similarity				
Post acquisition indicator	-0.371**	-0.371**	-0.278***	-0.278***
	(-2.21)	(-2.21)	(-2.97)	(-3.32)
Constant	1.161***	1.161***	1.112***	1.112***
	(7.36)	(7.75)	(14.03)	(18.05)
Acquisition Fixed Effects	No	Yes	No	Yes
Number of observations	63	63	63	63
Adjusted R^2	0.059	0.216	0.110	0.436

Table 5. Post-Acquisition Decline in Investments and Deals

(Robustness to Different Thresholds of Similarity)

The dependent variable in the panel A is the amount of VC investments in companies similar to the acquired one divided by all VC investments in early-stage deals in the software industry. The dependent variable in the panel B is the number of VC deals in companies similar to the acquired one divided by all VC early-stage deals in the software industry. In columns (1) and (2), a start-up is considered similar to the acquired company if it has a Pitchbook measure of similarity with the acquired company above 75%. The threshold is above 85% columns (3) and (4) and above 90% for columns (5) and (6). Post acquisition is an indicator variable that is equal to 1 in the 3 years after the acquisition. t-statistics are reported in parentheses, * $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

Pitchbook measure of similarity >	75%		85%		90%	
	Panel A: Relative Investment					
	(1)	(2)	(3)	(4)	(5)	(6)
Post acquisition indicator	-1.947*	-1.947***	-0.592***	-0.565***	-0.402*	-0.436**
	(-1.99)	(-3.86)	(-3.01)	(-3.05)	(-1.96)	(-2.10)
Constant	5.357***	5.357***	1.158***	1.146***	0.722***	0.736***
	(6.38)	(15.19)	(6.82)	(7.75)	(4.00)	(4.26)
Acquisition Fixed Effects	No	Yes	No	Yes	No	Yes
Number of observations	63	63	54	54	43	43
Adjusted R^2	0.052	0.808	0.133	0.347	0.070	0.275
	Panel B: Relative # of Deals					
	(1)	(2)	(3)	(4)	(5)	(6)
Post acquisition indicator	-1.600*	-1.600***	-0.329***	-0.306***	-0.0960**	-0.103***
	(-1.82)	(-4.61)	(-2.85)	(-3.72)	(-2.37)	(-3.24)
Constant	4.766***	4.766***	0.703***	0.692***	0.242***	0.245***
	(6.52)	(19.27)	(7.68)	(10.50)	(7.99)	(10.71)
Acquisition Fixed Effects	No	Yes	No	Yes	No	Yes
Number of observations	63	63	54	54	43	43
Adjusted R^2	0.045	0.883	0.126	0.608	0.111	0.554

Table 6. Restricting the Sample to Start-Ups That Are not Too Similar

The dependent variable in the columns (1) and (2) is the amount of VC investments in startup companies similar to the acquired one divided by all VC investments in early-stage deals in the software industry. The dependent variable in the columns (3) and (4) is the number of VC deals in companies similar to the acquired one divided by all VC early-stage deals in the software industry. A start-up is considered similar but not too similar to the acquired company if it has a Pitchbook measure of similarity with the acquired company between 75% and 85%. Post acquisition is an indicator variable that is equal to 1 in the 3 years after the acquisition. t-statistics are reported in parentheses, * $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

	Relative Investment		Relative # of Deals	
	(1)	(2)	(3)	(4)
Post acquisition indicator	-1.914*	-1.748***	-1.727*	-1.563***
	(-1.91)	(-3.69)	(-1.92)	(-4.76)
Constant	5.176***	5.103***	4.903***	4.830***
	(6.01)	(14.16)	(6.56)	(19.87)
Acquisition Fixed Effects	No	Yes	No	Yes
Number of observations	54	54	54	54
Adjusted R^2	0.058	0.828	0.060	0.897

Table 7. New Deals

The dependent variable in the columns (1) and (2) is the amount of VC investments in first financing deals in companies similar to the acquired one divided by the amount invested in all new early-stage deals in the software industry. The dependent variable in the columns (3) and (4) is the number of VC investments in first financing deals in companies similar to the one acquired, divided by the number of all new early-stage deals in the software industry. A start-up is considered similar to the acquired company if it has a Pitchbook measure of similarity with the acquired company greater than 80 %. Post acquisition is an indicator variable that is equal to 1 in the 3 years after the acquisition. t-statistics are reported in parentheses, * $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

	Relative Investment		Relative # of Deals	
	(1)	(2)	(3)	(4)
Post acquisition indicator	-0.418**	-0.376***	-0.601***	-0.534***
	(-2.42)	(-3.34)	(-2.77)	(-4.67)
Constant	0.997***	0.978***	1.445***	1.415***
	(7.04)	(10.35)	(7.85)	(15.88)
Acquisition Fixed Effects	No	Yes	No	Yes
Number of observations	58	58	58	58
Adjusted R^2	0.087	0.658	0.110	0.797

Table 8. Substitutes and Complements

The dependent variable in the columns (1) to (4) is the amount of VC investments in first financing deals in companies similar to the acquired one divided by the amount invested in all new early-stage deals. The dependent variable in the columns (5) to (8) is the number of VC investments in first financing deals in companies similar to the one acquired, divided by the number of all new early-stage deals. A start-up is considered similar to the acquired company if it has a Pitchbook measure of similarity with the acquired company greater than 80 %. The sample of acquired companies is split into substitutes and complements based on their complementarity with the acquirer company as classified in Table 1. Post acquisition is an indicator variable that is equal to 1 in the 3 years after the acquisition. t-statistics are reported in parentheses, * $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

| | Relative Investment | | | | Relative # of Deals | | | |
| | Substitutes | | Complements | | Substitutes | | Complements | |
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post acquisition indicator	-0.378**	-0.350***	-0.404	-0.404*	-0.461	-0.372***	-0.708**	-0.708***
	(-2.67)	(-3.92)	(-1.54)	(-1.89)	(-1.50)	(-3.03)	(-2.58)	(-3.68)
Constant	0.642***	0.628***	1.352***	1.352***	1.103***	1.061***	1.787***	1.787***
	(5.23)	(8.80)	(5.97)	(7.58)	(4.30)	(12.80)	(7.36)	(11.35)
Acquisition Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	30	30	28	28	30	30	28	28
Adjusted R^2	0.191	0.741	0.072	0.468	0.070	0.887	0.175	0.661

Table 9: All Software Acquisitions

The dependent variable in the columns (1) and (2) is the amount of VC investments in companies similar to the acquired one divided by all VC investments in early-stage deals in the same industry. The dependent variable in the columns (3) and (4) is the number of VC deals in companies similar to the acquired one divided by all VC early-stage deals in the same industry. A start-up is considered similar to the acquired company if it has a Pitchbook measure of similarity with the acquired company above 80%. Post acquisition is an indicator that is equal to 1 in the 3 years after the acquisition, Facebook/Google is an indicator that is equal to 1 if the acquirer is either Facebook or Google, and {post acquisition * Facebook/Google} shows the differential effect of an acquisition by Facebook or Google after the acquisition. t-statistics are reported in parentheses, * $p<0.10$, ** $p<0.05$, and *** $p<0.01$.

	Relative Investment		Relative # of Deals	
	(1)	(2)	(3)	(4)
Post acquisition indicator * Facebook/Google indicator	-0.676	-0.649**	-0.721*	-0.689***
	(-1.34)	(-2.07)	(-1.78)	(-3.22)
Post acquisition indicator	-0.367	-0.322***	-0.183	-0.148**
	(-1.41)	(-3.51)	(-0.85)	(-2.30)
Facebook/Google indicator	-1.792***		-1.269***	
	(-4.30)		(-3.76)	
Constant	4.390***	4.288***	3.415***	3.341***
	(25.24)	(70.00)	(24.68)	(90.77)
Acquisition Fixed Effects	No	Yes	No	Yes
Number of observations	1285	1285	1285	1285
Adjusted R^2	0.012	0.892	0.010	0.926