Kill Zone

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Abstract

We study why acquisitions of entrant firms by an incumbent can deter innovation and entry in the digital platform industry, where there are strong network externalities and some customers face switching costs. A high probability of an acquisition induces some potential early adopters to wait for the entrant's product to be integrated into the incumbent's product instead of switching to the entrant. Because of this, the incumbent is able to acquire the entrant for a lower price. Even if the incumbent platform does not undertake any traditional anti-competitive action, the reduction in prospective payoffs to entrants creates a "kill zone" in the space of startups, as described by venture capitalists, where entry is hard to finance. The drop-off in venture capital investment in startups in sectors where Facebook and Google make major acquisitions suggests this is more than just a theoretical possibility.

There is a growing worry that digital platforms (multi-sided markets that offer digital services to customers, often for free) 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. This is not just a theoretical possibility. 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]

The notion that platform 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?

We first check if there is more than anecdotal evidence of a "Kill Zone", sufficient to warrant a theoretical analysis. 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. This could, of course, be consistent with a number of explanations. To probe deeper, we conjecture that when a major acquisition by an incumbent platform is not blocked by the antitrust authorities, it signals there is a higher likelihood that other similar acquisitions will not be blocked. Under this assumption, a testable consequence of the existence of a "Kill Zone" is that the acquisition of an important new entrant by an incumbent digital platform can lead to a decrease in new entry and a decrease in the amounts invested in early-stage enterprises that are similar to the entity acquired.

To test this, we collect data on the number of deals and dollar amounts invested by venture capitalists in a sector around the time major acquisitions by Facebook and Google are announced in that sector (a more detailed explanation of the data sources and the figures discussed in the introduction follow in Section 1). In the three years following an acquisition by Google and Facebook in a certain industry sector, VC investments in that sector (normalized by total investments in the software industry) drop by over 40% (see Figure 2a) and the number of deals falls by over 20% (see Figure 2b).

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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

Is this a common phenomenon in all software acquisitions? When we compare VC investments in companies similar to the target after a Google or Facebook acquisition with VC investments in companies similar to the target after an acquisition by any other software company, we find that investments drop more after a Google or Facebook acquisition (see Figures 2a and 2b). Thus, consistent with the idea of a "Kill Zone", there seems to be something special about acquisitions by multi-sided platforms that deters further investment in that space.

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 platform settles on a 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 qualitatively similar. After a number of other robustness checks, we are unable to rule out the possibility of the existence of a kill zone. We therefore turn to a possible theoretical explanation.

We argue that the standard economic argument (of acquisitions incentivizing entry) relies critically on the acquisition price for firms being adequate compensation for innovation. This may not hold in the context of acquisitions by digital platforms, because the economics of digital platforms differs significantly from the textbook neoclassical economics of firms. To show this, we build a simple model of platform competition that contains the key novel ingredients present in this space: First, platforms are multi-sided. On one side, the platform serves customers who are not charged any explicit fee for services. On the other side, it deals with advertisers, who pay for access to customers. 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, customers start out with the incumbent (an immense incumbency advantage in the presence of network externalities). Finally, some agents have switching costs.

In this context, we show that a crucial role in the success of an entrant offering platform services is played by early adopting app designers (we will suggest alternative types of early adopters later). Each app designer has a cost of adapting their app to the new platform, a switching cost that will be recovered only if the platform is above a certain quality. If the cost of adopting the new platform varies across app designers, it is straightforward that the higher the quality of the entrant, the more the number of app designers who will adopt it. The mass of adopting app designers, in turn, drives the adoption by ordinary customers for two reasons. First, the mass of adopting designers 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 – clearly, the more the apps on the entrant platform, the higher its utility to the ordinary customer.

The adoption decision by the app designer is crucial. Importantly, it is greatly affected by the ease with which acquisitions are cleared by the Federal Trade Commission. If an app designer expects the new platform to be acquired soon, they will be reluctant to pay the adaptation costs, unless the new platform is of significantly higher quality than the incumbent one. After all, they know that if the entering platform's technology is a net improvement over the existing technology, the incumbent will integrate it smoothly with the existing platform, with new features melded with old features so that existing apps work seamlessly without any additional costs. Thus, the expectation of a merger soon after entry will dissuade many designers from incurring the additional cost to adapt their apps to the entrant platform. In turn, the low number of apps on the entrant will deter many ordinary customers from adopting it.

The stand-alone market value of the entrant platform represents the entrant's reservation value in any bilateral merger negotiation with the incumbent. It will be critical in determining the acquisition price. Since value in the multi-sided platform comes from advertisers, who will pay for the customers they can access, the entrant's stand-alone value will be driven by the total number of customers who adopt it. Yet, this number depends crucially on the number of app designers who adopt it, which in turn depends on the expectation this platform would indeed stand alone. Thus the prospect of a quick acquisition can sufficiently reduce adoption by designers, and hence by customers, so as to reduce the payoff from the merger and discourage entry.

Put differently, think of early-adopter designers 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 bees' welfare. The same is true here. Any environmental condition that reduces the app designers' incentives to switch to better platforms has a negative effect on the system.

If it is so important for an entrant to signal that it will not sell out to the incumbent, why doesn't it 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 egoistic CEOs/founders, driven more by a vision than by money, can be interpreted as their attempt to commit credibly to never sell the platform. So can the prevalence of the dual class share structure that entrusts the founders with ultimate control. 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).

It would be premature to draw any policy conclusion on antitrust enforcement based solely on our model and our limited evidence. 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 stand-alone valuation of new entrants, stimulating investments in

technological improvements and entry. These restrictions on mergers will, however, have costs: if the market remains segmented, network externalities will be lower than otherwise achievable, and some customers will not enjoy a superior technology. 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.

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 its platform, this expectation alone will decrease the value of any new entrant. In turn, this will discourage entry. The point in our paper is that exclusionary conduct may simply occur by the very nature of online platforms, network externalities, and switching costs, without the incumbent engaging in explicit anti-competitive actions. Indeed, the very act of liberalizing the take-over regime can be anti-competitive. Importantly, the effects of some traditional anti-competitive actions can be magnified. For example, the creation of any artificial switching cost can have a disproportionate effect on deterring new investments.

Our model can help us think of policies that may increase innovation in digital platforms, if the concerns about a "Kill Zone" are warranted. 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 on 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

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cost" effect. By increasing the payoff of incremental innovation, mergers reduce the additional payoff of radical innovation. Callander and Matouschek (2020) reach a similar result by focusing on rent seeking. With incremental innovation, the entrant's product is closer to the incumbent's business, and is more liable to be taken over when mergers are allowed (so that the incumbent can shut down a competitive threat). In our model we only have 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 stems from 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, platform acquisitions – and explains why the analysis and outcomes may be different there.

Cunningham, Ederer, and Ma (2018) 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 (2019) and Hylton (2019)).

In the legal 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. Unlike Khan, we do not focus on the anti-competitive actions of incumbents but suggest the

nature of platforms may have a chilling effect nevertheless. Wu (2018) 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. While this is a different point to the one we make, the notion that new technologies create new ways that competition can be affected is similar.

Finally, Bryan and Hovenkamp (2019) 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 discuss the evidence in section 1, outline the model in section 2, present the analysis in section 3, discuss alternative assumptions in section 4, discuss possible extensions in section 5, and then conclude.

1. The Data

To investigate the possibility of a "Kill Zone", 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 (for our analysis), we have not observed any such decision yet. Therefore, we need a different strategy.

We focus on completed acquisitions. All major acquisitions are reviewed by the US Federal Trade Commission (FTC). That a large transaction is not blocked sends a powerful signal that other similar transactions will be allowed. In particular, we analyze the effects of Facebook and Google's acquisitions of large software companies from the beginning of 2006 to the end of 2018. We focus on Facebook and Google because they are two prominent incumbent multi-sided platforms that charge a zero monetary price to ordinary customers. We restrict attention to their major acquisitions because their clearing the FTC review conveys a stronger signal of the FTC's likely attitude towards similar acquisitions in the future. Finally, we focus on software companies because we are looking for start-ups that can develop into potential substitutes (or complements as we see later) to 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 satisfy these criteria: 7 by Google and 2 by Facebook. We list them in Table 1. We also list whether these acquisitions are broadly substitutes or complements to the platform's business, an issue we will elaborate on later.

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.[2] 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 that is not 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 of the 9 acquisitions – the 3 years before the acquisition year + the acquisition year + the 3 years after. So we should have data on similar start-up companies for 63 observation years. 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 similar 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 comparison set consists of up to 480 companies, possibly increasing the noise. For this reason, we start with an initial threshold of 80%

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

similarity. With this threshold, we have no treated company in only three observation years, which we drop from the sample.

1.1 Main Results

Recall that in Figure 1 we plotted 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's acquisition of WhatsApp, and the amount invested peaks shortly after, in 2016. The decline over time can be driven by many factors, including factors that are common to other software acquisitions (such as a change in financing conditions or economic outlook). 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% or higher Pitchbook similarity (see above) to 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, which we label relative investment, is expressed in percentage terms. 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. The software industry exhibits a strong downward trend of relative investment in the three years before an acquisition, a trend that is reversed in the three years after the acquisition, unlike the continued downtrend when a platform acquires.

In Figure 2b, we plot the normalized relative number of startup investments. The pre-event trend decline in the relative number of deals is not surprising. In early stages, 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. 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.

In Table 2, we report 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 in that year. Table 2 also reports the summary statistics for new investment deals (first stage investments in the similar startups).

In Table 3 we substantiate Figure 2 with regressions. 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 relative investment is 2.1 percent (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 (necessary 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 percent (see Table 2), this is 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 percent, this corresponds to a 36% drop. Introducing a fixed effect for each of the nine acquisitions (column 2) does not change the estimated coefficient, but 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 in magnitude 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 one acquired experienced a significant drop in investments and number of financing deals after Facebook or Google undertook a major acquisition.

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 3 OA in the online appendix shows.

1.2 Similarity

In Table 4A, 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%. The effect of acquisitions on the number of deals, reported in Table 4B, is similar.

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. 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%. The results in Table 5 are similar to the ones in Table 3. There is a quantitatively large drop in investments and deals after an acquisition even in this not-too-similar set.

Even if acquisitions deter new investments, a VC firm 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 6 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.

1.3 Including all acquisitions

It is possible that in nascent industries all acquisitions by a powerful incumbent make future quality improvements less likely and thus innovation in the same industry segment less profitable. If this is the case, we should observe the same post-acquisition drop in other industries as well. To check whether this is indeed the case, in Table 7 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. As control variables we have a dummy for the post-acquisition period, a dummy for the post acquisition period interacted with an indicator if the acquisition is made by Google or Facebook, and acquisition fixed effects.

All segments of the software industry seem to experience a decline in investment in comparable firms after an acquisition, as reflected in the negative and significant coefficient for the post acquisition indicator. Yet, we are primarily interested in the coefficient of the post-acquisition indicator interacted with the Facebook/Google indicator. 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.

In column 2 we repeat the same analysis with the number of deals as dependent variable. Once again, the interaction term has a large, negative, and statistically significant coefficient.

In sum, Table 7 suggests 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 thrice as large for Facebook/Google deals, and the decline in deals is over 5 times larger than for an ordinary software acquisition, suggesting the problem is more severe. There is then merit in exploring a model of platform acquisitions that would account for such a phenomenon.

2. The Model

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 is θ. There are two sets of agents that are relevant to platforms: *app designers* with measure λ and *ordinary customers* with measure 1. All agents are risk neutral and maximize expected utility, and the per-period gross discount rate is 1. We consider three relevant dates in the first period, 0, ½, and 1, and then *n-1* periods after that, where *n* is the total life of the technology (we elaborate shortly). Both app designers and ordinary consumers are initially on the incumbent platform.

2.1. App designers

At date 0 (the beginning of the first period), there is a buzz about the entrant's arrival, and all app designers observe a common signal about E's quality increment relative to I, where every app designer's posterior belief of quality after observing the signal is distributed normally with mean q and precision α.

App designers can choose to adapt their app to the entrant platform after observing the signal. Clearly, app designers will be motivated by the commercial prospect of attracting ordinary customers on the entrant platform (see shortly) as well as the sheer technical joy of producing a better product. For now, we will assume that if an app designer adapts, so long as she has some possibility of attracting some customers who will allow her to demonstrate the apps' use, she gets a per-period incremental utility equal to the incremental technical quality θ of the platform – she is primarily technically minded. We could allow her utility to be some other linear or non-linear functions of quality, but all that is important is that it be increasing in θ. When we discuss robustness, we will discuss the possibility that the app designer may be commercially minded.

Each app designer *i* faces a one-time adaptation cost s_i to adapt her app to the new platform. We assume s_i is uniformly distributed over $[0, \bar{s}]$. Note that for simplicity, we give all app designers the same posterior expectation of quality and vary their adaptation costs. It will turn out that only the difference matters, so all app designers could have the same adaptation costs and different posterior expectations of quality, or some combination thereof.

If app designers adapt, they will "multi-home" – they will service ordinary customers on both platforms. We explore the consequences of single homing in the robustness section.

2.2. Ordinary Customers

Ordinary customers usually devote little attention to the capabilities of the platform they are on or the apps they use – in the spirit of Kahneman (1973), attention has to be selective given the effort it requires, and the platform plays a useful but only modest role in a customer's life. However, attention can be drawn by a salient stimulus or cue (see Fiske and Taylor (1991) or Hirshleifer and Teoh (2003)). The buzz associated with the new entrant platform is one cue which causes ordinary customers to pay attention to relative platform capabilities, to acquire information, and to make a decision to switch (or not) to the entrant platform and the apps on it at date ½. They have two pieces of information at that time: i) they observe how many app designers switched at date 0[3] ; 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. In practice, the ordinary customer's switching cost is likely to be low so we set it to zero, though a positive number is easily handled. The real difficulty in getting customers to consider switching platforms and/or apps is to get their attention, which attenuates after the early buzz.

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[3] In practice, this will reflect the write-ups by the tech correspondents of various newspapers, magazines, or informative websites. Nothing would change if the ordinary customers saw the same signal that app designers see.
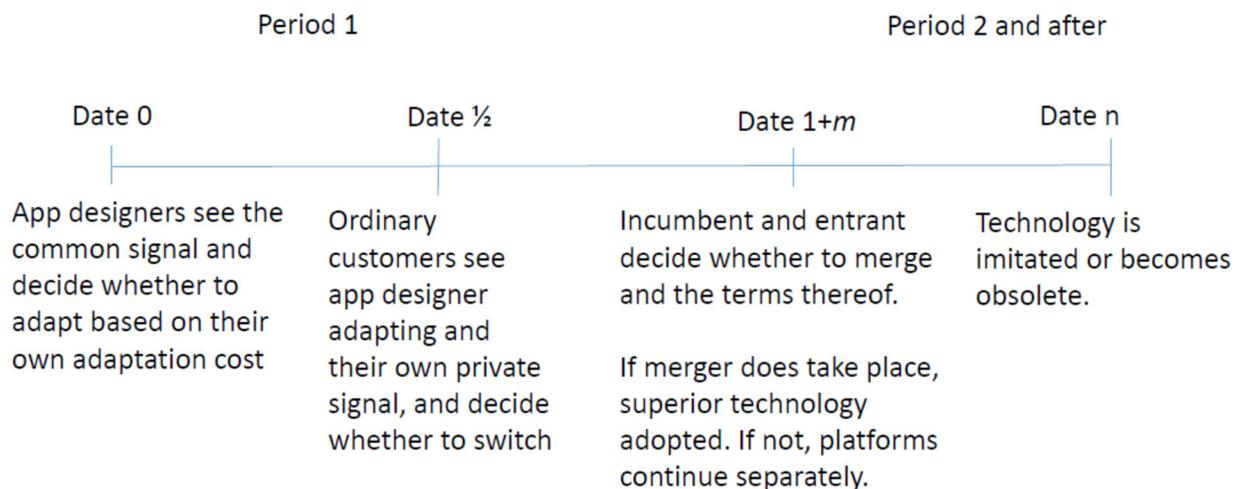
Ordinary customers experience network externalities – they are better off the more apps they have access to on a platform, and the more ordinary customers that are on it. Specifically, for an ordinary customer the benefit of a platform is given by the sum of its expected quality, the mass of app designers who have apps on it, and the mass of ordinary customers who opt for it. Ordinary customers do not want the effort of multi-homing – once they switch, they devote themselves to the new platform.

At date 1+*m*, the two companies decide whether to merge or not after due diligence on one another. After due diligence, the companies know the true θ. 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. The acquirer in the merger ensures a seamless interface for all apps to the superior technology, regardless of whether they adapted earlier or not, so adaptation costs are zero at that point. All apps and their customers now enjoy the superior technology.

The parameter *m* proxies for the liberality of the anti-trust regime, with *m=0* indicating the FTC blesses any proposed merger quickly and *m=n-1* indicating it never approves over the life of the technology. If the two companies do not merge, they will survive a further $n - (1 + m)$ periods independently with their different technologies. Note that *n* reflects the technology's natural life before new innovation displaces it, or the degree of patent protection of the new technology. If the incumbent can copy the new technology right away, $n = 1$, and merger policy will be irrelevent. In what follows, we will assume the non-trivial case, $n > 1$.

Since the non-occurrence of the merger is a non-event, ordinary customers' attention is not roused. They have no inclination to gather information or re-examine their choices.

The timeline is as follows

Period 1		Period 2 and after	
Date 0	Date ½	Date 1+*m*	Date n
App designers see the common signal and decide whether to adapt based on their own adaptation cost	Ordinary customers see app designer adapting and their own private signal, and decide whether to switch	Incumbent and entrant decide whether to merge and the terms thereof. If merger does take place, superior technology adopted. If not, platforms continue separately.	Technology is imitated or becomes obsolete.

2.3. Value of Entrant

The platform service is given for free to ordinary customers in exchange for their data. Thus, a platform's profits derive from the revenues a platform can get on the advertising side. In turn, the value of a platform to advertisers is a function of the number of customers a platform has: more customers on the platform means more eyeballs that will see the advertisement and more customers also mean more platform data and thus better targeted advertising. The combination of these factors implies that if $V^E(p)$ is the value of the entrant platform to advertisers, where p is the fraction of ordinary customers on it, then $\dfrac{dV^E(p)}{dp} > 0$. Thus, the value of the platform to advertisers need not be a direct function of the quality of the platform θ, which only affects customer experience, but it may be an indirect function through the number of ordinary customers the platform can attract. We assume the platform extracts all the value from advertisers.

3. Analyzing the Model

We now determine the measure of app designers that adapt their app to the new platform, and its effect on switching behavior by ordinary customers. This will then affect the price that the incumbent will offer the entrant to merge. We postpone discussion of the merger for later.

In the presence of network externalities, customer choice is usually difficult to model because of the possibility of multiple equilibria – if the customer believes everyone will switch to an entrant, she has an incentive to switch, and if she believes no one will switch, she will not switch. To finesse this problem, we use the technique of global games (for an excellent overview, see Morris and Shin (2003)).

3.1. Analysis of Switching Behavior

In equilibrium, it will turn out that the merger always takes place at $1+m$. In making their decision at date 0, app designers will compare their expected incremental utility from adapting, $(1+m)q$, with their individual adaptation cost. Thus, an app designer will switch if and only if

$$(1+m)q > s_i. \tag{1.1}$$

Given that app designers' adaptation cost is uniformly distributed, the measure of app designers who switch in the first period is given by $\lambda \dfrac{(1+m)q}{\overline{s}}$ if $0 \le \dfrac{(1+m)q}{\overline{s}} \le 1$, 0 if $\dfrac{(1+m)q}{\overline{s}} < 0$ and λ otherwise.

To simplify the notation in the rest of the paper we will assume that $0 \leq \dfrac{(1+m)q}{\bar{s}} \leq 1$.[4] Clearly, the

longer the period m that the firms will remain independent, the longer each app designer who switches enjoys the incremental quality of the entrant, and the more the fraction of app designers who find it worthwhile to incur adaptation costs. The measure of app designers who remain with the incumbent is

$$\lambda[1 - \frac{(1+m)q}{\bar{s}}].$$

At date ½, ordinary customers observe how many app designers have switched. Since they know m, they can back out q, the app designers' posterior expectation of θ. Combined 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 $\alpha + \beta$. The ordinary customer's decision to switch will affect his utility for ½ $+m$ periods if a merger takes place (or more in the out-of-equilibrium outcome that no merger takes place). His decision depends upon (i) his posterior belief of the quality differential between platforms (ii) his estimate of the size of customers who will choose each platform and (iii) the measure of app designers who have adapted to the new platform. Specifically, he will switch if and only if the network-externality-adjusted quality of the entrant is superior, that is, iff

$$\rho_i + p(\rho_i) + \frac{(1+m)\lambda q}{\bar{s}} \geq (1 - p(\rho_i)) + \lambda \qquad (1.2)$$

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 app designers who have already adapted. 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 total measure of app designers. Notice that this stems from the assumption that app designers will multi-home, so an ordinary customer who stays on the incumbent platform will have access to all of the apps. The sum on the right hand side represents the network externalities from staying with the incumbent. This inequality can be rewritten as

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

---

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

3.2. The Time ½ Switching Equilibrium

The ordinary customer's decision problem is typical for a global game (see, for example, Morris and Shin, 2000, 2003), and allows us to obtain a unique equilibrium.[5] To solve it, we first conjecture that ordinary customers will follow a switching strategy where they switch if their expectation 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 the fraction p that will switch 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 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 $\Pr\{\rho_j \leq \rho_i \mid \rho_i\} = \Pr\{\dfrac{\alpha q + \beta x_j}{\alpha+\beta} \leq \rho_i \mid \rho_i\} = \Pr\{x_j \leq \rho_i + \dfrac{\alpha}{\beta}(\rho_i - q) \mid \rho_i\} =$

$\Pr\{\eta_j \leq \rho_i + \dfrac{\alpha}{\beta}(\rho_i - q) - \theta \mid \rho_i\}$. This simplifies to

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

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

$$\rho^* + 2p(\rho^*) + \frac{(1+m)\lambda q}{\overline{s}} - (1+\lambda) = 0 \tag{1.3}$$

or

$$\rho^* + 2\Big(1 - \Phi\big(\gamma(\rho^* - q)\big)\Big) + \frac{(1+m)\lambda q}{\overline{s}} - (1+\lambda) = 0 \tag{1.4}$$

$$\rho^* + 2 + \frac{(1+m)\lambda q}{\overline{s}} - (1+\lambda) - 2\Phi\big(\gamma(\rho^* - q)\big) = 0 \tag{1.5}$$

---

[5] We structure it as a global game to obtain a unique solution. Without the global game structure we would have to focus on an arbitrarily chosen equilibrium.

Let $S(\rho) = \rho + 2 + \dfrac{(1+m)\lambda q}{\bar{s}} - (1+\lambda) - 2\Phi\big(\gamma(\rho-q)\big)$. 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 $\dfrac{dS(\rho)}{d\rho} > 0$

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

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

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

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

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

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

QED

3.3. Merger Regime and Comparative Statics

We are interested in how changes in the merger regime affect outcomes. A liberal merger regime would set *m=0*, allowing mergers to take place as soon as possible. A regime that is opposed to mergers will set $m \geq n-1$, that is, not allow mergers so long as the technology is valuable. So a decrease in *m* implies a more liberal merger regime.

The following figure shows the variation of optimal switching point for $\lambda = 0.4$, $\bar{s} = 2$, $\alpha = 300$, $\beta = 100$, $\theta \in [0,1]$. For a given *m,* we can see that as app designers' quality expectation, *q*, increases, the optimal switching point for ordinary customers decreases. Furthermore, for a given *q*, the optimal switching point decreases as *m* increases since more app designers switch for any given *q*.

Optimal Switching Point for $\lambda = 0.4$
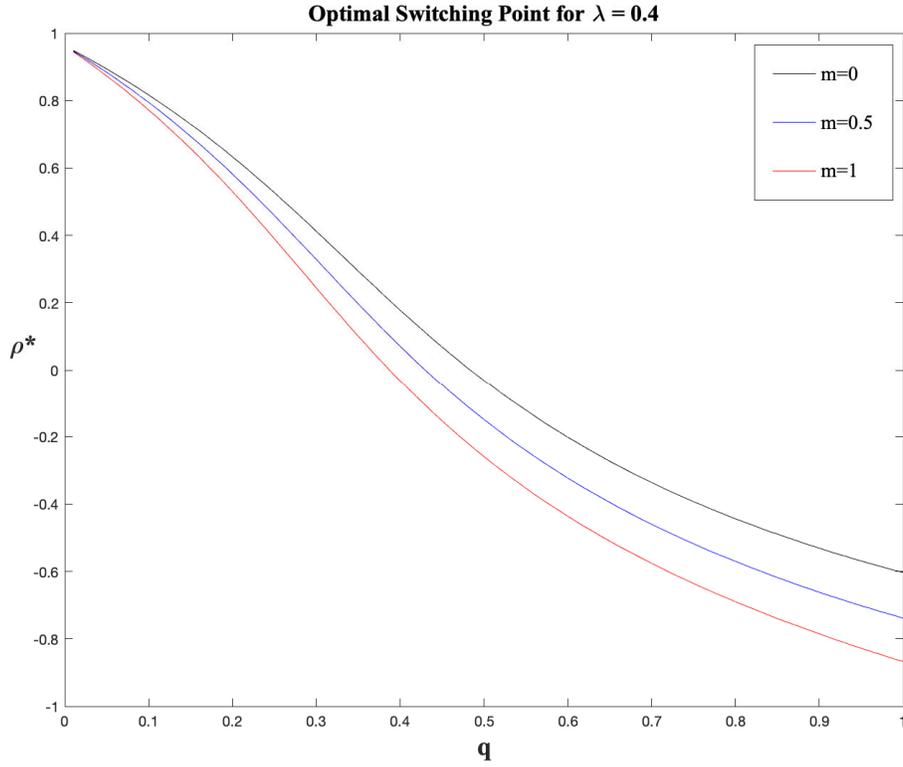
This chart immediately suggests the following corollaries:

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 app designer expects the entrant to remain independent.

Proof: Totally differentiating $S(\rho^*) = 0$ given q, we get

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

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

Intuitively, the longer the period the firms will remain independent, the more app designers will switch to the entrant for a given positive app designers' quality expectation *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.

Corollary 2: The optimal switching point decreases and the fraction of ordinary customers switching to the new technology increases with a higher app designer expectation of quality, *q*.

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

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

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

The following figure presents the above two results with $p(\rho^*)$ being the proportion of ordinary customers shifting to the new technology. For $\lambda = 0.4$, $\overline{s} = 2$, $\alpha = 300$, $\beta = 100$, $\theta \in [0,1]$.

$p(\rho^*)$ for $\lambda = 0.4$
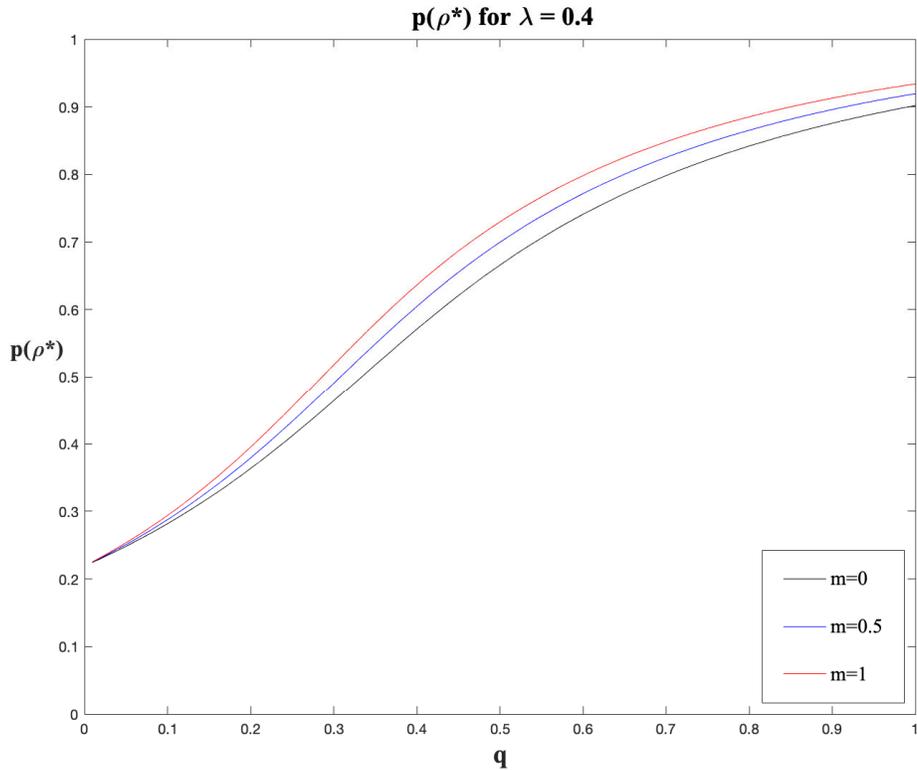
3.4. The Bargaining over the Merger.

Let us now turn to discussing the bargaining over the merger. Before we do that, though, we need to settle one issue. Clearly, if a merger will take place at date 1 with *m=0*, neither the ordinary customer nor the app designers have any decisions to make. What about the out-of-equilibrium possibility that bargaining breaks down and the merger does not take place?

As stated earlier, since the non-occurrence of the merger is a non-event, ordinary customers' attention is not roused. They have no inclination to gather information or re-examine their choices. Given

no hope of attracting ordinary customers if they adapt, app designers will also not revisit their adaptation choice, which was made with the equilibrium outcome in mind.

Let us now compare two regimes. In the liberal regime, the merger takes place at date 1, so $m=0$. In the second, mergers are prohibited so $m=n-1$. Let $V(1)$ be the discounted sum of profits that a merged platform with all the customers and the superior technology extract in the advertising market after a merger at date 1. Let p be the proportion of ordinary customers who switch to E at time ½. Let $V^I(1-p)$ and $V^E(p)$ be the value respectively of the incumbent and of the entrant, operating for the remaining $n-1$ periods as stand-alone platforms. Since a monopolist's profit is greater than the sum of the profits of two duopolists, $V(1) > V^I(1-p)+V^E(p)$, and the two platforms are better off merging. Since both I and E know θ, bargaining will take place under symmetric information and thus it will lead to the efficient outcome. The only question is at what price.

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. So μ is the bargaining power of the incumbent. The entrant's payoff in case of merger is

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

where p^M is the proportion of ordinary customers who switched based on the app designers' 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.
In case we are in the regime where mergers are prohibited, the payoff of the entrant from date 1 is

$$\Pi^E(p^{NM}) = V^E(p^{NM}).$$

Note that $E_0\left[V^E(p^{NM})\right] \geq E_0\left[V^E(p^M)\right]$ where E_0 denotes expectation at date 0. The inequality holds because $n > 1+m$, so $p^{NM} > p^M$ because of Corollary 1. Intuitively, when mergers are prohibited, more app designers will adapt to the entrant, which will mean that more ordinary customers will switch to the entrant platform, giving it greater stand-alone value. Hence, if the entrant's bargaining power is zero (that is, $\mu=1$), its expected 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.

More generally, if its bargaining power is small, the entrant's payoff will be driven mostly by its outside option. Since we just showed that its 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. With sufficient uncertainty on when and whether a merger will take place, the app designers will be prompted to adapt, increasing the value of potential entrants.

There is a more general point here. Entrants who anticipate being acquired have to focus not just on the incremental new technology they bring to the merger but also on ways to preserve their standalone value (so as to extract more in the merger negotiations). In our model, that stand alone value is augmented by the customers they attract. Interestingly, though, the stand-alone value need not enhance the combined value, and any costly action taken to augment the stand-alone value is wasteful rent seeking. Nevertheless, it may be necessary to enhance the acquisition price and thus increase the incentives for innovation.[6]

3.5. Ex Ante Investment

Thus far, we have assumed that the entrant's technological improvement θ was manna from heaven. More realistically, this improvement is the result of some ex-ante investment in innovation 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, it will draw a technology of quality θ from a distribution. Before it decides whether to enter, E will compare its expected profit with its known cost of R&D and enter if and only if

$$E_0[\Pi^E(\theta)] > C^E. \tag{1.6}$$

Prohibiting acquisitions by incumbent platforms can have the effect of increasing the expected profit of new entrants for any θ (for example, if incumbents have tremendous bargaining power so that $\mu \to 1$ in the merger negotiations). This will increase the range of C^E that are viable, and increase the probability of investment in R&D and thus entry.

Theorem 2: So long as the expected measure of app designers switching with a prohibition on mergers is positive, there is a $\hat{\mu} \in [0,1]$ such that for incumbent bargaining power $\mu > \hat{\mu}$, the probability a new platform enters the market is higher when mergers are prohibited than when they are not.

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[6] The additional cost of such entrant actions to protect their property rights, including possibly wasteful innovation around the incumbent's patents so as to be able to create a standalone business, would imply that the cost of innovation is lower to the incumbent than to the entrant; the latter has to go the extra mile to extract a higher acquisition price from the incumbent. This is one more reason why permitting mergers tends to favor the incumbent.

Proof: See proof in the online appendix section A1.1.

Notice that this result could hold even when prohibiting acquisitions is socially inefficient because it prevents mergers that are ex-post efficient. 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. From *Theorem 2,* it follows:

Corollary 3: So long as the expected measure of app designers switching with a prohibition on mergers is positive and the incumbent bargaining power $\mu > \hat{\mu}$, any event increasing the probability that a merger will be allowed will decrease the probability of a new platform entering.

Proof: Let π denote the probability that a merger will be allowed. Then the expected profits of a new platform at time 0 is given by

$$E_0[\Pi^E(\theta)] = \pi E_0^M[\Pi^E(\theta)] + (1-\pi)E_0^{NM}[\Pi^E(\theta)]$$

The effect of π on the expected profits, $E_0[\Pi^E(\theta)]$, is given by

$$\frac{\partial E_0[\Pi^E(\theta)]}{\partial \pi} = E_0^M[\Pi^E(\theta)] - E_0^{NM}[\Pi^E(\theta)]$$

From Theorem 2, for the incumbent bargaining power $\mu > \hat{\mu}$, we have $E_0^{NM}[\Pi^E(\theta)] > E_0^M[\Pi^E(\theta)]$. This implies

$$\frac{\partial E_0[\Pi^E(\theta)]}{\partial \pi} < 0$$

This implies that the range of C^E that are viable for a new platform decreases as the probability π increases. Hence the probability of a new platform entering is decreased by any event that increases the probability that the merger will be allowed.

3.6. Determinants of Bargaining Power

Corollary 3 states that if the incumbent's bargaining power is sufficiently large, an increase in the probability of a merger should reduce entry. What can we say about the incumbent's bargaining power?

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First, in a standard Rubinstein (1981) game, each party's bargaining power is inversely related to its degree of impatience or effective 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 has the ability 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 it 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 using its lobbying power. Most (if not all) these behaviors could be deterred by an active antitrust authority, but the recent record on this front in the United States has been quite weak.[7] The awareness of this 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.

Finally, a caveat. Notice that within our model a lower incumbent bargaining power μ will always improve efficiency, since it will not affect decisions ex post, but it will increase entrant 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.

4. Alternative Assumptions and Robustness

We have made a number of assumptions in deriving the results. They include (i) app designers face adaptation costs, (ii) customers care about network externalities, (iii) the platforms are multi-sided. Which of these assumptions are crucial for the results, and which ones are for plausibility? Would alternative assumptions also work? These are the questions we turn to in this section.

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[7] See, for example, the battle between Quidsi and Amazon detailed in Khan (2017) and Stone (2013).

4.1. Network Externalities

Start first with the assumption that customers care about network externalities. How important are these. Let the network externalities associated with a unit measure of customer and app designer be ζ (we have assumed $\zeta = 1$ thus far). It is easily seen that equation (1.5) determining the switching point now becomes

$$\rho^* + \zeta\left[2 + \frac{(1+m)\lambda q}{\overline{s}} - (1+\lambda) - 2\Phi\left(\gamma(\rho^* - q)\right)\right] = 0$$

So if there are no network externalities, that is, $\zeta = 0$, the switching point becomes $\rho^* = 0$. This makes sense. Were it not for network externalities, ordinary customers (who have no switching costs) would simply opt for the platform they expect to be better, based on their private signal and the signal gleaned from app designer choices. However, any change in merger regulation will have no effect in this case since the mass of app designers moving, $\frac{(1+m)\lambda q}{\overline{s}}$, has no effect on the switching point when $\zeta = 0$, other than revealing what q is (for more detailed comparative statics, see the online appendix).

4.2. Assumptions about the app designers

Setting the network externalities associated with a unit measure of customers, ζ, back to 1, we can vary the importance of the network externalities associated with just the app designers by varying their measure λ. It is easily seen in equation (1.5) that m drops out when $\lambda = 0$, so changes in merger regulation do not affect the optimal switching point. This should be intuitive – changes in merger regulation affect the app designer's adaptation decision, which affect the measure of app designers that switch, and thereby, through the resulting network externalities, the attractivenes for the ordinary customer to switch. If the measure of app designers is zero, the app designers' adaptation has no effect on an ordinary customer's switching decision. So changes in merger regulation have no effect.

We could consider alternative interpretations for the early adopter. The app designer is isomorphic to a content creator or influencer who can adapt his content to the entrant platform if his expectation of the quality of the entrant platform is high enough. The early adopter could also be a technology influencer, whose main role is to ascertain the quality of the entrant platform and transmit this information to the ordinary customer by switching, even while contributing to network externalities by being a customer themselves.

We have assumed the app designer's utility of adaptation is increasing in the technical quality of the entrant platform. The easiest interpretation is that the app designer has a technical aesthete where they

care primarily about the degree to which the platform enhances the performance of their app (which is why they need some customers). Similarly, the content creator or influencer may care about the features of the entrant platform that allow them to interact better with their audience. We could alter the model so that their utility depends also on commercial considerations such as the number of ordinary customers on the platform. In this case, their adaptation decision would also become a function of p, the expected measure of ordinary customers that will switch. However, at date 0, p is monotonically increasing in the expected quality, q. In principle, therefore, this will increase the complexity of equation (1.5) determining the switching point without changing its fundamental characteristics.

We have assumed that the app designers can multi-home. Our model can easily handle the case they do not. The ordinary customer switches now if

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

The difference from the earlier inequality (1.2) is in the last term on the right hand side where we recognize that those app designers who switch do not benefit the incumbent's ordinary customers any more. Multi-homing could be prohibited by the platforms themselves, or if supporting an app on a platform requires significant resources so that each designer can choose to be on only one. It is easily shown (see online appendix section A2.3), ceteris paribus, that the ordinary customer's switching point is higher when multi-homing is allowed – intuitively, the incumbent platform becomes more attractive since it retains the services of any apps who choose to adapt to the new entrant also. As a result, entry becomes more difficult.

4.3. Assumptions for plausibility or simplicity.

Some assumptions in the model are for plausibility. Note that ordinary customers back out q from the fraction of app designers that switch, and this occurs regardless of the size of λ. Does q need to be informative? Clearly, app designers are experts and they should know something about the relative quality of the entrant. But what if they do not and the precision α of the app designers' beliefs tend to zero. Clearly, since q represents all the information that app designers have about relative quality no matter how imprecise, they would still switch, comparing their expected utility on adaptation (which is proportional to q) against their adaptation costs. So there would still be network externalities caused by app designer adaptation, and merger regulation would still have effect. However, ordinary customers would put very low weight on q and much more weight on their private signal x_i in arriving at their

posterior expectation of quality ρ_i.[8] As a result, any change in q will have a more muted effect on the

optimal switching point ρ^* as q becomes less informative. In sum, a more permissible merger regime still

reduces switching by ordinary customers even if app designer adaptation conveys no information – it is

the app designer-induced externality that is critical.

What about network externalities for ordinary customers? This is in the model entirely for

plausibility – it would be strange for ordinary customers to experience network externalities from app

designers (or technological influencers) but not from each other. However, if we assume there are no

network externalities associated with ordinary customers, (1.5) simplifies to $\rho^* + \dfrac{(1+m)\lambda q}{\overline{s}} - \lambda = 0$.

The equilibrium switching point falls with m and q as before.

We have assumed low switching costs for ordinary customers for simplicity. This is easily

handled in the model by adding such a cost s^C to equation (1.3) so that it becomes

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

Essentially, this will raise the switching threshold, lower the number who switch, and lower the

probability of entry.

We also assumed that ordinary customers do not become attentive after date ½ and thus do not

switch later. For many new products (say a book), the maximum interest is during the early buzz when

customers are willing to find out more about it, hence the marketing adage "You never get a second

chance to make a first impression." The consequence is that app developers also have no reason to change

their decision at future dates.

In a more general model with commercially minded app designers, the stickiness of ordinary

customers to platforms after the early decision could result in app designers having a higher value to

adapting early to the entrant.[9] Early adapters would easily retain on their app any of their ordinary

customers who switch to the entrant platform. Furthermore, they would attract switching customers who

were using apps that have not been adapted to the entrant. If the designer adapts to the entrant at a later

date, though, all the ordinary customers that switched earlier to that platform would have found new apps.

If these customers have switching costs, it would be harder to attract a sizeable clientele, even if some

ordinary customers can still be picked off. Put differently, the later an app designer adapts to an entrant,

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[8] Conversely, if the app designers are experts, q very informative and the private signal much less so, q would be much more influential in altering the optimal switching point.

[9] One other reason why early adaptation may be more valuable than late adaptation is the finite life of the technology. Clearly, if the adaptation decision is considered after the merger fails, there is less time for the app designer to amortize the adaptation costs. Indeed, if there is only one period or less left (n=2), the app designers will never change the decision they made at date 0.

the more the mass of ordinary customers who switch to the entrant have settled down with early adapters, and the less beneficial adaptation will be. This will mean that app designers have little incentive to switch later, even if new information comes their way.

4.4. Multi-Sided Platforms

We have assumed multi-sided platforms. Clearly, different users -- app designers, advertisers, and ordinary customers – see different aspects of the platform. Importantly, that the platform is multi-sided explains why a group of users does not internalize what the platform does with another group. For instance, if the platform harvests more data and is able to sell targeted ads at a higher price to advertisers, the welfare of ordinary consumers is not affected. This is consistent with the apparent behavior of most customers, who do not perceive the cost of giving away their data.[10]

Implicit in this separation is the idea that platforms cannot charge a negative price, that is, subsidize customers to join them. Traditionally, platforms have not paid customers, but recently several companies have tried to find ways around this constraint. There are three major obstacles to paying customers for using a platform. First, transactions costs can quickly mount, since each transaction tends to have a very low value. Second, there is the risk of abuse: for example, 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.[11] To get around the afore-mentioned problems, Brave chose to pay users with its own 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 mitigate coordination problems.

A more effective alternative to paying customers is to pay app designers to switch to the new platform. Of course, if it is known that designers are paid, the type of quality inference ordinary customers make when they observe adaptation by an app designer is very different from the one assumed in our model. Moreover, this solution assumes that the entrant platform knows exactly who are the app

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[10] Here we assume that targeted ads increase the efficiency of advertising, without affecting the welfare of the people targeted. We could also assume that the platform extracts back some fraction of the utility customers get by giving advertisers access. So long as the fraction is not greater than or equal to 1, and so long as it is constant across platforms, we could allow ordinary customers to internalize the cost of advertising without changing the results.
[11] https://www.wired.com/story/brave-browser-will-pay-surf-web/.

designers who need to be paid. In practice, a new entrant might not know what kind of app customers will want. Any uncertainty about this will either increase the cost of paying for app designer to adapt or decrease the probability this strategy will succeed (or both). Finally, while the possibility of paying for ordinary customers or app designers might reduce the frequency with which superior entrants fail to overcome incumbents, it does not eliminate the fundamental problem. In fact, it could exacerbate the reduction in the incentives to invest in innovation. In particular, suppose that after paying the cost C^E to enter the market, the entrant will engage in Bertrand competition with the incumbent to pay the app designers. Given the status quo advantage (as well as the larger capital hoard) the incumbent enjoys, the new entrant would have to pay a large share of its ex-post profits to defeat the incumbent. This payment will greatly reduce (and possibly eliminate) the profitability of the project, leading to less innovation and entry.

4.5. Substitutes and Complements

We have assumed the entrant offers a substitute product to the incumbent. 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 is Youtube to 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 micro-target 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 platform with a new one.

By this light, 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 entry 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, advertisers). 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 it obtains (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 for these complements vigorously in order to compete effectively with the platform that has already bought one. The net effect on acquisition prices and investment is ambiguous.

In sum, we have shown that a greater tolerance for mergers can hurt investment in innovation by potential entrants if they are substitutes to the incumbent platform. This result may hold even if the entrant is a complement to the incumbent platform.

In Table 1, we classified the 9 acquisitions as either substitutes or complements based on the discussion above. Some classifications are easy. 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. Postini and Apigee are similar. Postini is 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 is an Application Programming Interface management and predictive analytics software provider, again very useful to the Google experience but not a potential substitute for Google.

Other classifications are more difficult, further complicated by the multi-market nature of these platforms, especially Google. Google not only offers search services, but also email services (Gmail), navigation services (Google Maps), and travel 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., travel. 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.

We now check whether their effects are different. In Table 8, we split the sample based on our classification of complements and substitutes (see Table 1). 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).

5. Policy implications and Extensions

5.1 Benevolent Planner Solution

It is well-known that in the presence of network externalities, the competitive solution is not necessarily Pareto optimal. If a central planner had the power to transfer the new technology to the incumbent (to avoid switching costs), then the solution that maximizes welfare is for all customers to stay with the incumbent and get the new technology if $\theta > 0$. Assuming that the new technology does not affect the efficiency of advertising, incorporating advertising does not change the conclusion.

A central planner would like the new technology to be introduced whenever the expected value it creates exceeds the cost, C^E, of generating it. In short, introduce whenever

$$E_0\left[\theta(1+\lambda)\right] > C^E. \tag{1.7}$$

Note that (1.7) is very different from (1.6). A central planner would like a new technology to enter the market whenever the value it creates exceeds the cost of generating it. By contrast, an incumbent will enter the market only if the value she can appropriate is greater than the cost of innovating.

In this welfare analysis we have assumed the central planner can allocate the technology to the incumbent at no cost. The plausibility of this assumption strongly depends upon the nature of the switching costs, which we will discuss in the next subsection.

5.2 Interoperability

A crucial friction in our model is the barrier between different platforms. If there were none, network externalities would cease to matter, and so would the effect described in our model.

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The assumption of barriers is realistic in many situations but is not always driven by technological considerations. One cannot post family pictures at one locations so that they show up on Facebook and Snapchat. Yet, these technological limits can easily be overcome if the companies want to. For example, Power Ventures, a small California startup, offered a single site for its customers to see all of their friends, regardless of the social media they were using. In 2008, Facebook sued Power Ventures, and it closed.[12] Perhaps then, barriers between platforms serve to enhance incumbency advantage. This phenomenon is true even in the absence of network externalities (Edlin and Stiglitz (1995)), but its effects are greatly amplified in the presence of network externalities.

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. Something similar 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, if not eliminated.

In our model, 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. Conversely, any powerful incumbent's action to reduce interoperability might warrant anti-trust scrutiny.

5.3 Anti-Trust Policy

The market solution leads to excessive entry or excessively low entry depending on whether $E_0[\Pi^E(\theta)] > or < \theta(1+\lambda)$. In the former case, prohibiting mergers would only exacerbate excessive entry, in the latter case it would improve desirable entry. Yet, it would do so at the cost of two inefficiencies, ex post. First, consumers will be split between two platforms, not fully enjoying the network externalities. Second, the advertising market will be segmented, losing some of the economies of scale. Thus, prohibiting mergers would be welfare enhancing if and only if the benefit created by the additional entry exceeds the sum of these two inefficiencies. The overall welfare implications of prohibiting mergers consequently depends on the relative importance of ex-ante underinvestment vis-à-vis ex-post inefficiency.

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[12] https://www.eff.org/cases/facebook-v-power-ventures.

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 the 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. As the model suggests, increasing interoperability is a preferable approach.

5.4 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 entrants have to customer data, the more they can fine-tune their products, leveling the playing field with the incumbent. Thus, the default allocation of data ownership crucially influences competition and innovation. Rules that allow incumbent platforms free use of their accumulated data make it easier for the incumbent to exploit their network externalities, not just in their main line but also 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.

5.5 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, innovation incentives will be more muted if intellectual

property is not protected. 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 (2019)). 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.

5.6 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. Its recent ban on a variety of dominant Chinese platforms like ByteDance's Tik Tok seems to have led to a number of domestic startups attracting investment.[13] 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. 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

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[13] "India Takes a Risk by Encouraging National Interest", by Henny Sender, Financial Times, July 14, 2020, https://www.ft.com/content/a147fe8c-0ab3-460f-b9e2-f4d51a545085

industry in the United States. Of course, all the traditional caveats associated with the infant industry argument still pertain here.

6. Conclusions

Venture capitalists claim that acquisitions in the start-up space done by powerful incumbent platforms, such as Facebook and Google, create a "kill zone." 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 a function not only of the technological difference of the new platform, but also of its persistence as independent entity. Since a merger immediately transmits the superior technology to everybody, it reduces the benefit of adoption for early adopters. The prospect of a merger reduces adoption, making it harder for a technological superior entrant to acquire ordinary customers. This difficulty in acquiring customers reduces the stand-alone price of any new entrant, decreasing the price at which they can be acquired and thus reducing their incentive to innovate.

It would be wrong to conclude from our analysis that all acquisitions from incumbent platforms should be prohibited, since there is a trade-off between static efficiency (the consumer welfare created by mergers) and dynamic efficiency (incentives to innovate). We argue that mandating interoperability eliminates this trade-off, increasing welfare.

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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 dollar amount of funding going to early-stage financings of start-ups in the social media space. Source: Pitchbook.

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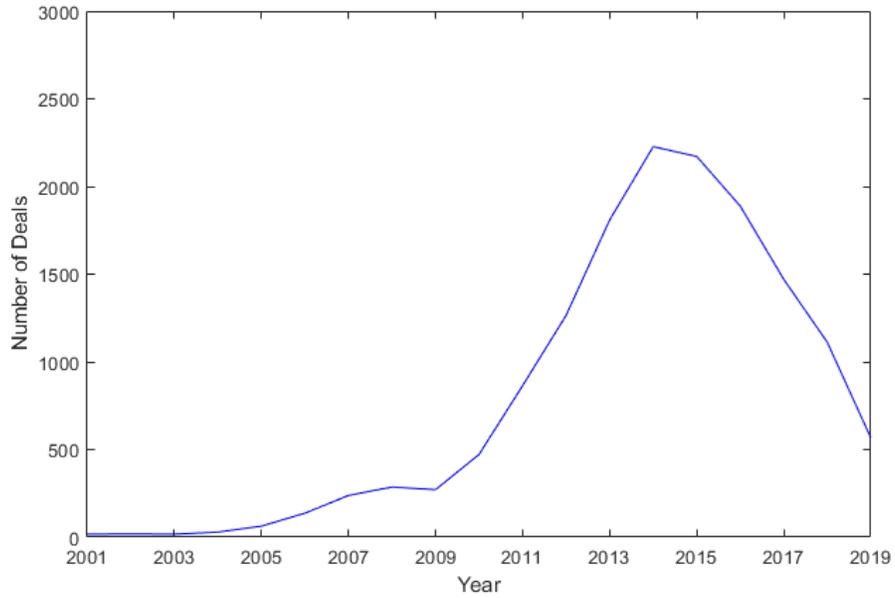
(b) Investment: Dollar amount financed (in million $)

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 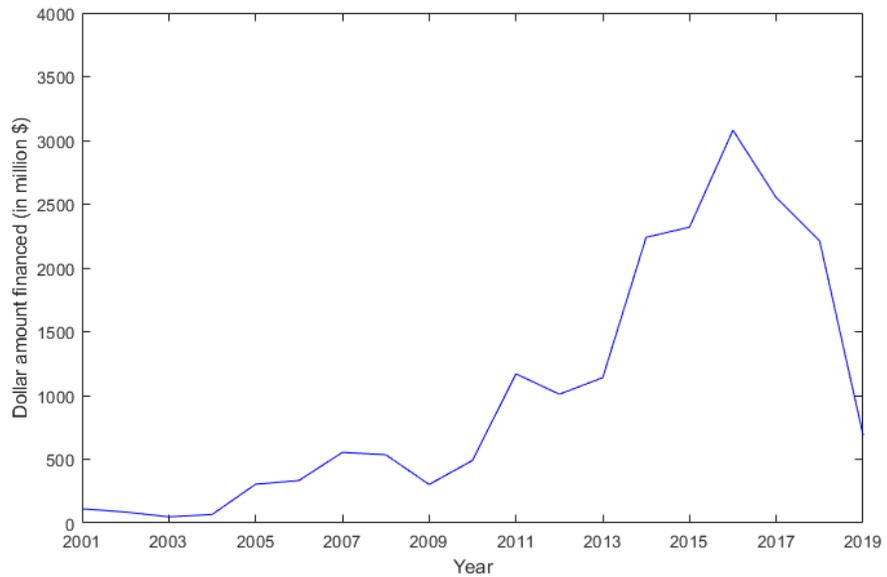cyclicality, the amount of investments in comparable "treated" companies is divided by all VC investments in early deals in the software industry made in the same year. This ratio, relative investment, is then normalized by the relative investment in the year of the acquisition, so that the normalized 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
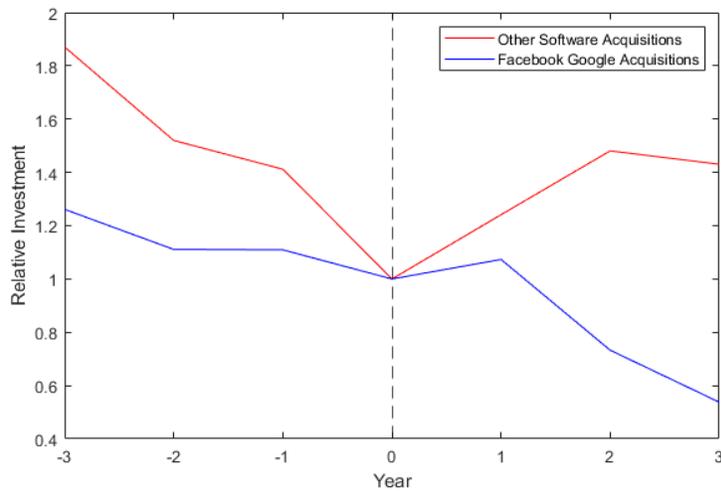
   (b)   Normalized relative number of deals before and after an acquisition
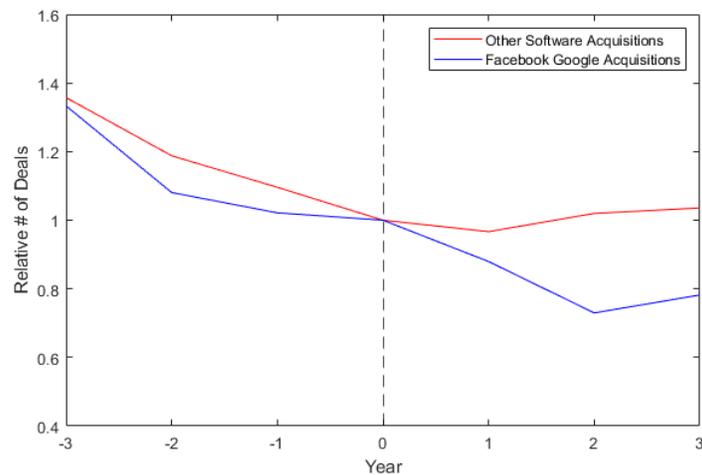
Table 1. Acquisitions Considered

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), (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) we divide the acquisitions into complements and substitutes (see Table 1).

Variable	Mean	St Dev	Min	25th	50th	75th	Max	Obs
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 deal	2.5	2.0	0.1	0.7	2.2	3.7	7.8	63
Number of comparison companies	93.1	119.7	2	19	36	131	480	63
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 deal	4.1	3.8	0.0	1.8	2.4	6.7	17.7	63
Number of comparison companies	153.7	169.2	1	36	98	213	746	63
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 deal	1.7	1.5	0.0	0.6	1.5	2.3	8.4	60
Number of comparison companies	72.0	79.8	1	19	34	84.5	282	60
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 deal	0.6	0.5	0.0	0.2	0.5	0.8	2.6	54
Number of comparison companies	28.2	37.4	1	5	10.5	35	121	54
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 deal	0.2	0.1	0.0	0.1	0.2	0.3	0.5	43
Number of comparison companies	10.5	12.0	1	1	4	18	41	43
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 deal	4.1	3.5	0.2	1.5	2.3	7.0	15.2	54
Number of comparison companies	28.2	37.4	1	5	10.5	35	121	54
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 deal	1.2	0.9	0.0	0.4	1.1	1.5	4.2	58
Number of comparison companies	56.9	65.2	1	11	26	69	235	58
Substitute								
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 deal	0.9	0.9	0.0	0.3	0.5	1.3	3.0	30
Number of comparison companies	60.8	72.4	1	5	32	69	235	30
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 deal	1.5	0.9	0.2	0.9	1.4	1.7	4.2	28
Number of comparison companies	52.6	57.4	10	16	22	81.5	167	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 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 column (1), 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% in column (2) and above 90% in column (3). 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)
Post acquisition (dummy)	-1.947***	-0.565***	-0.436**
	(-3.86)	(-3.05)	(-2.10)
Constant	5.357***	1.146***	0.736***
	(15.19)	(7.75)	(4.26)
Acquisition Fixed Effects	Yes	Yes	Yes
Number of observations	63	54	43
Adjusted R^2	0.808	0.347	0.275
	Panel B: Relative # of Deals		
	(1)	(2)	(3)
Post acquisition (dummy)	-1.600***	-0.306***	-0.103***
	(-4.61)	(-3.72)	(-3.24)
Constant	4.766***	0.692***	0.245***
	(19.27)	(10.50)	(10.71)
Acquisition Fixed Effects	Yes	Yes	Yes
Number of observations	63	54	43
Adjusted R^2	0.883	0.608	0.554

Table 5. Restricting the Sample to Start-Ups That Are Not Too Similar

The dependent variable in the column (1) 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 column (2) 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)
Post acquisition (dummy)	-1.748***	-1.563***
	(-3.69)	(-4.76)
Constant	5.103***	4.830***
	(14.16)	(19.87)
Acquisition Fixed Effects	Yes	Yes
Number of observations	54	54
Adjusted R^2	0.828	0.897

Table 6. New Deals

The dependent variable in the column (1) 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 column (2) 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)
Post acquisition (dummy)	-0.376***	-0.534***
	(-3.34)	(-4.67)
Constant	0.978***	1.415***
	(10.35)	(15.88)
Acquisition Fixed Effects	Yes	Yes
Number of observations	58	58
Adjusted R^2	0.658	0.797

Table 7: All Software Acquisitions

The dependent variable in the column (1) 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 column (2) 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)
Post acquisition indicator * Facebook/Google indicator	-0.649**	-0.689***
	(-2.07)	(-3.22)
Post acquisition indicator	-0.322***	-0.148**
	(-3.51)	(-2.30)
Constant	4.288***	3.341***
	(70.00)	(90.77)
Acquisition Fixed Effects	Yes	Yes
Number of observations	1285	1285
Adjusted R^2	0.892	0.926

Table 8. Substitutes and Complements

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. 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. 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	
	Substitute	Complement	Substitute	Complement
	(1)	(2)	(3)	(4)
Post acquisition (dummy)	-0.350***	-0.404*	-0.372***	-0.708***
	(-3.92)	(-1.89)	(-3.03)	(-3.68)
Constant	0.628***	1.352***	1.061***	1.787***
	(8.80)	(7.58)	(12.80)	(11.35)
Acquisition Fixed Effects	Yes	Yes	Yes	Yes
Number of observations	30	28	30	28
Adjusted R^2	0.741	0.468	0.887	0.661