Tech Giants and New Entry Threats

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Abstract

The prominence and perceived power of tech giants—Amazon, Apple, Facebook, and Google—have raised antitrust concerns in stifling new startup entries, the so-called kill zone effect. We provide evidence showing that such an allegation is real as the entrants of tech giants’ product spaces have a significantly lower (higher) likelihood of receiving second round VC financing and exiting using IPOs (being inactive or defunct) relative to benchmark entrants in recent years. However, tech giants experience more new startup entries than an average tech incumbent. Tech giants’ acquisitions also do not show the same entry deterrence effect as other benchmark giants. Furthermore, tech giant entrants tend to attract investments from reputable venture capitalists. These results suggest that the kill zone effect, despite its existence, is not a serious concern yet.

Keywords: New Entry, Startups, Venture Capital, Antitrust, Competition, Tech Giants

1. Introduction

On July 29th, 2020, four chief executives—Amazon’s Jeff Bezos, Apple’s Tim Cook, Facebook’s Mark Zuckerberg, and Google’s Sundar Pichai—testified before a congressional antitrust panel, which opened an investigation to examine whether these tech giants have engaged in anti-competitive tactics that damage smaller rivals and stifle innovations (TheWashingtonPost 2020). Although the accusations ranging from antitrust concerns, stealing rivals’ data, to political censorship, in this study, we focus on the so-called “kill-zone” effect (TheEconomist 2018).

Practitioners and academia have expressed concerns that the capacity for tech giants to imitate the innovations of entrants and to acquire some of them prematurely for the purpose to stifle their growth will lower the value of innovations. Venture capitalists have avoided these startups in the technology sectors leading to a lower incentive of new entry. Nonetheless, these entry deterrence strategies are not new; giant such as Microsoft has been through similar allegations in the 90’s (See Klein (2001) and Gilbert and Katz (2001)) for more discussions on the Microsoft case). Tech giants were, at one point, startups themselves. It is common for acquirers to outsource R&D (Higgins and Rodriguez 2006) or restructure acquired businesses to exploit their comparative advantages (Maksimovic et al. 2011). Acquisitions of startups also allow emerging technologies to be scaled up faster in the hand of resourceful incumbents. However, Cunningham et al. (2021) document intentional killer acquisitions of innovative entrants to prevent the development of competing products in the pharmaceutical industries. Segal and Whinston (2007), however, point out the tension of antitrust restrictions that the same restrictions aim to protect entrants can reduce their expected profits once a successful entrant becomes the dominant firm leading to a lower level of innovation.

In this study, we first study VC funding characteristics and exit potential of individual startups pursuing different entry strategies defined by the product spaces of tech giants and comparable benchmarks. We then analyze the extent of new startup entries of incumbents over
time. We attempt to assess whether the kill-zone effect is pervasive. To analyze the kill-zone effect, we use a text-mining approach that compares the product descriptions of the incumbents with those of the new entrepreneurial startups to construct several measures that quantify the extent of entry of a startup into different incumbent groups’ product spaces. Specifically, these entry measures invert the new entry threat measure (NET) first proposed by Pan et al. (2019). They compute similarity scores by mapping an incumbent’s product descriptions in its 10-K filings to those of new startups that receive first-round VC funding at the seed or early stage recorded in Thomson Reuters VentureXpert database during the same calendar year.

Consistent with the kill zone hypothesis, tech giant entrants have a significantly lower chance of receiving next round financing relative to benchmark entrants with an estimated probability of 4% reduction for a one standard deviation increase in entries. Conditional on receiving next round VC financing, there are no significant incremental differences in VC funding characteristics across periods except for the size of VC syndicates.

Our paper contributes to growing concerns of the dominance of tech giants and their effects on market structures, entries of startups, and VC financing. The complexity of our results is consistent with the nature of the topic. We should consider the issue not only for specific outcomes given entries but also in the context of overall startup entries.

2. Related Literature

Literature has documented that it is the VCs rather than the entrepreneurs that play an important and, in many cases, dominant role in making corporate decisions for the startups (e.g., Gorman and Sahlman, 1989; Kaplan and Stromberg, 2001). When it comes to innovation in the U.S, VC investment is associated with more patent counts and citations (Lerner 2000). It contributes to the leading roles of US firms in the technology sectors (Gompers and Lerner 2001). Sorenson (2007 empirically shows that VCs achieve these effects—measured by the success of a startup’s exit using IPO—through their abilities to screen projects (selection) and to add values (influence), particularly, more experienced VCs. Therefore, if tech giant entrants attract experienced VCs, receive larger amounts of funds, have a higher chance of receiving next round, and have exit potentials other than being acquired by tech giants, then the kill zone allegation may not be a serious concern.

Several studies have attempted to investigate the kill zone effects. Oliver Wyman (2018), commissioned by Facebook, examines the trend of VC investments at the sector levels and concludes that the investment activities, M&As, R&D, and venture investing of tech giants, have no negative impact on VC investments. Different from the above approach, our analysis is firm specific. Therefore, the results and conclusions can be very different from a macro level assessment. Another related study is by Kamepalli et al. (2020, who document significant declines in VC investments in startups that are in the same (or similar) space as the company acquired by Facebook and Google. Our study complements theirs because we look at all startups that received first round VC funding at the seed or early stage with specific entry strategies. We analyze not only the amount and likelihood of next round funding but also who invested in these startups and their exit potential.

3. Data and Empirical Design

The datasets that we use are constructed using multiple sources. We focus on the firms in the High Tech industries (Hecker 2005) identified by 46 4-digit NAICS industry codes and firms classified as high-tech industry upon their IPOs in the SDC Platinum (Thomson Reuters) new issue database. Financial data and other firm characteristics are obtained from Compustat. Our entry
variables are the invert of the new entry threats adopted from Pan et al. (2019), who describe such threats as emerging from venture-funded startup firms and measure them using a text-mining approach that compares the product descriptions of the incumbents with those of the new entrepreneurial startups. VC and startup information is obtained from the SDC VentureXpert database of Thomson Reuters.

The primary startup sample consists of 17,922 firms that received first round VC financing at the seed or early stage from 1995 to 2018. The incumbent sample contains 5088 publicly traded firms (with total assets information) over the fiscal years from 1995 to 2018 constituting 40472 firm-year observations, representing an unbalanced panel. The sample period includes years when there was considerable turbulence in High Tech sector (e.g., the Internet boom and bubble burst), the period of the global financial crisis in 2008 and the recovery afterwards, as well as the less volatile years.

3.1 Measuring the Startups’ Entry Strategies

We first discuss the measure of incumbents’ new entry threats. We extend the text similarity measures from previous studies (Hoberg and Phillips 2016; Pan et al. 2019). Here, the similarity score between each pair of startup and incumbent is used to measure a startup’s entry strategy in terms of an incumbent’s product space. To capture meaningfully the startup entries, we only consider startup entries in the IT sector. Each year, we code entry equals one if the similarity score is above the 80 percentile of all scores of that year. Entries into other benchmark incumbent groups are calculated similarly.

3.2 Tech Giants and Benchmarks

There is no clear rule how one can classify tech giants. We take the obvious approach to define Amazon, Apple, Facebook, and Google as tech giants in this study because they are the focus of recent antitrust investigations. The remedy is forming other tech giants as benchmarks to serve as comparison groups. It is also interesting to see whether the actions of other giants should raise similar concerns regarding new entries activities.

To ensure that we include other largest tech firms, we start from the components of S&P 500 index and restrict firms in the communication services or information technology sectors based on the Global Industry Classification Standard (GICS). We then rank these firms based on total assets and market values at the end of 2018 fiscal year. The business lines of market value benchmarks appear to be closer to those of tech giants. Therefore, we use this list, which includes Microsoft, Visa, Verizon, Intel, AT&T, Cisco Systems, Oracle, Adobe, Salesforce.com, and IBM.

3.3 Characteristics of VC financing and Exits

For each startup in our sample, we identify the VC firms provided the first round seed or early stage financing. We calculate two VC reputation/experience variables—one for near term, i.e., VC firm round counts within prior three calendar years, and one for longer term, i.e. VC firm age. Tian (2012) summarizes several measures used in the literature that can be grouped into deal counts, aggregate amounts invested, or funds raised since 1965. Alternatively, some use a shorter term, such as prior 5 years. Finally, VC firm’s age is also commonly used.

A VC specialized in earlier stage may not invest as much as a later stage VC but a lot more rounds. Early stage VCs are also more influential in selecting which startups to receive first round funds. VCs’ ability to screen constitutes, on average, two thirds of value created by VCs (Sorensen 2007). For our purpose, round counts are more appropriate than amounts. We use prior three years round counts to capture recently active and successful VCs and supplement this reputation variable by VC age, which, by definition, captures the experiences that accumulate overtime.
We follow our sample startups until the end of October 2020 in VentureXpert database and identify their exit types as IPO, merger, and defunct. The defunct status is incomplete in VentureXpert. We include a startup in the defunct category if it not receiving VC financing within 5 years after its last VC financing round.

3.4 Empirical Model

To test the kill zone hypothesis, we use a sample of startups receiving first round seed or early stage financing from 1995 to 2018 in the IT industries. Because the allegations of antitrust issues are recent, so we use a difference-in-differences (DID) approach to analyze the kill zone effects by comparing the results across subperiods surrounding 2008 and between the entrants of tech giants and those of ten benchmark giants. We use the following model specification:

\[ Y_i = \alpha + \beta_1 \text{Entry-Giant}_i + \beta_2 \text{Entry-Bench10}_i + \beta_3 \text{Entry-Giant}_i \times \text{Post}_i + \beta_4 \text{Entry-Bench10}_i \times \text{Post}_i + \delta \text{X}_i + \epsilon_i \]  

(1)

where \( Y_i \) is the dependent variable. Depending on the analyses, it could be VC funding characteristics or exit outcomes. “Entry-Giant” and “Entry-Bench10” and their interactions with “Post” are the key explanatory variables that we use to compare the startups pursuing different entry strategies surrounding 2008. If the kill zone effect is unique for tech giants, we should observe systematic changes in the variables of interest across time relative to the benchmarks. This model specification also allows us to compare the differences in entrants of tech giants or those of benchmarks to the base comparison startups. \( X_i \) is a vector that contains startup and VC characteristic control variables, which include several state dummies that have considerable numbers of startups. Yearly fixed effects are included but not reported for brevity. Finally, \( \epsilon_i \) is the idiosyncratic component.

3. Main Results

The findings on exits reported in Table 1 strongly support the kill zone hypothesis. The tests of DID indicate that, relative to benchmark entrants, tech giant entrants experience a significant decline in the likelihood of IPO and a significant increase in that of being defunct or inactive. The results are not only highly statistically significant but also economically meaningful. A one standard deviation increase in “Entry-Giant” reduces the chance of IPO by 1.9% and increases that of defunct by 2.6%, while the corresponding numbers for benchmark entrants are 1.65% and -3.6%, respectively. Therefore, the net effect for IPO is -3.55% and that for defunct is 6.2%. Startups pursuing the product markets of benchmark giants in the earlier period have a significantly higher tendency of being acquired relative to tech giant entrants. However, such a difference is not significantly different during the later period.

Table 2 reports a truncated version of analysis on new entry threats of incumbents for the next three years following the time we measure explanatory variables. We ask two questions: (1) whether tech giants experience higher new entry threats than benchmark giants surrounding 2008; (2) whether tech giants’ M&A activities produce more deterrent effects than other benchmark giants. The DID tests indicate no significant differences between tech giants and benchmarks for both questions. However, it worth mentions that both tech giants and benchmarks have significantly higher new entry threats than the base comparison groups, but it is only significant for tech giants during the earlier period and that for benchmarks during the later period.

In addition, both groups’ M&As demonstrate significant increases in new entry deterrence, which diminishes the positive effect of giants’ M&As on new entries while leads to a significantly negative impact of benchmarks’ M&As on new entries. Since M&As by incumbents in the technology sectors, in general, have a significantly positive impact on new entries. Therefore, the
4. Conclusion

In this paper, we evaluate the concerns of the alleged kill zone effect of tech giants in a holistic framework. We find evidence consistent with the kill zone hypothesis. However, it is not pervasive because tech giants have significantly higher new startup entries relative to an average IT incumbent. Tech giants’ acquisitions also do not have a significant entry deterrence impact on startups though it declines from a previously significantly positive effect. In contrast, the acquisitions of benchmark giants’ exhibit significant entry deterrence in the later period.

Nonetheless, the kill zone effect is real. We document significant declines in the probabilities of second round VC financing and IPO exit among tech giant startups relative to benchmarks. Tech giant entrants are also more likely to become inactive or defunct during the later period than benchmarks. However, tech giant entrants tend to attract reputable VCs, particularly during the later period. Reputable VCs are more resourceful. They also exhibit better screening capacity. Their interests in tech giant entrants can mitigate the kill zone concerns.

Taken together, our findings suggest that the kill zone exists but its overall impact is not pervasive as of the evidence presented so far. However, it does not preclude the possibility that serious negative impacts could emerge later. Given the importance of the issue, it warrants ongoing monitoring and we believe that the analytical framework proposed in this study is a suitable one to use.

References


### Table 1 The Likelihood of Exit by Type: Multinomial Logit Regressions

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<thead>
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<th>VARIABLES</th>
<th>Coefficients</th>
<th>Marginal Effects</th>
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*, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, for a two-tailed test.

### Table 2 New Entry Threat (NET): Random Effects Panel Regressions

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<th>Base Group:</th>
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<td></td>
<td>(1)</td>
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<tr>
<td>t+1</td>
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<td>t+2</td>
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