Tech Giants and New Entry Threats

Abstract

Tech giants like Amazon, Apple, Facebook, Google, and Microsoft have drawn antitrust concerns due to their perceived power, potentially stifling new startups, especially through the so-called kill zone within their product domains. This study demonstrates that tech-giant entrants face a significantly lower likelihood of obtaining follow-on financing and achieving long-term survival in recent years. However, such phenomena are transitory and concentrated among tech-giant entrants lacking patents and operating within segments characterized by high network effects. There is no evidence that the M&As conducted by tech giants deter entries. Furthermore, tech giants experience more entries compared to the average tech incumbent.

Keywords: Startup New Entry, Venture Capital, Antitrust, Kill Zone, Tech Giant.

1. Research Overview

On July 29, 2020, the chief executives of Amazon, Apple, Facebook, and Google testified before a congressional antitrust panel, which investigated allegations of anti-competitive tactics by these tech giants that harm smaller rivals and stifles innovation.[1] Practitioners and academia have expressed similar concerns (Lemley & McCreary, 2019). A study by Zhu and Liu (2018) focuses on Amazon's entry into third-party sellers' product spaces and find that affected small suppliers experience halted growth on the platform. After Snap Inc. rejected Facebook's acquisition bid in 2013, Facebook launched apps that resembled Snap's popular features. Some venture capitalists (VC) claimed that they have since avoided nascent startups in the product spaces of tech giants, resulting in a decrease in VC funding known as the "kill zone" effect.[2]

Nonetheless, these entry deterrence strategies mentioned above are not new; giants like Microsoft faced similar allegations in the '90s (Gilbert & Katz, 2001; Klein, 2001). They did not prevent the rise of new tech giants like Google and Facebook, which were once startups themselves. Snap also became a unicorn, going public in 2017 with an estimated market value of $34 billion.[3] In contrast, Salesforce acquired workplace software company Slack for a substantial $27.7 billion.[4] These anecdotes call for a systematic evaluation of the alleged kill zone and its potential channels.[5] Despite intense media coverage and regulatory attentions, we have not found other study that comprehensively assesses this topic within a holistic framework.

One major challenge that we face is defining tech-giant entrants, as commonly used industry classifications like SIC codes lack the necessary granularity. Further complication arises because tech giants have expanded into diverse conglomerates. For example, Amazon operates not only as an online shopping site but also as a tech service provider for numerous businesses. To address this challenge, we employ a text-mining approach inspired by the product similarity score used in Hoberg and Phillips (2010, 2016). We extend this method by comparing the product descriptions in an incumbent's 10-K filings with the business descriptions of startups that receive initial-stage VC funding in the same calendar year. The degree of overlap between the business descriptions of two firms determines the similarity score. If a startup's similarity score with an incumbent is no less than the 90th percentile of the yearly sample, we consider it an entrant in the incumbent's product space. Consequently, we can determine whether a startup has entered the product domains of tech giants and examine its susceptibility to the kill zone effect.

Comparing tech giants to average IT firms would be inappropriate due to the inherent differences between these two groups. Hence, we establish another benchmark using five large tech incumbents referred to as "bench giants," which closely compete with tech giants and have their entrants' business segment distributions most similar to tech-giant entrants' business segments. These entrants should encounter

[1] Amazon, Apple, Facebook and Google grilled on Capitol Hill over their market power, https://www.washingtonpost.com/technology/2020/07/29/apple-google-facebook-amazon-congress-hearing/ (last accessed: Jan. 25, 2022).

[2] See several quotes of venture capitalists in the article "American tech giants are making life tough for startups," The Economist, June 2, 2018, https://www.economist.com/business/2018/06/02/american-tech-giants-are-making-life-tough-for-startups (last accessed: Jan. 25, 2022).

[3] See the article "Snapchat shares surge 44% in market debut," the Wall Street Journal, March 2, 2017 (last accessed: Mar. 3, 2022).

[4] See the article "Salesforce to Acquire Slack for $27.7 Billion," the New York Times, December 1, 2020 (last accessed: Mar. 3, 2022).

[5] It is debatable whether Microsoft should be grouped with Amazon, Apple, Facebook, and Google as tech giants. We perform tests using only Microsoft entrants relative to bench-giant entrants and find similar results. The results also show that Microsoft entrants appear to have the same fate as other tech-giant entrants.

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comparable economic environments and challenges. By examining systematic differences between tech-giant entrants and bench-giant entrants over time, we can determine whether the kill zone phenomenon is specific to tech giants.

Using this innovative measure to define entrants, we analyze a sample of startups in the information technology (IT) industries from 2005 to 2018 to investigate the kill zone hypothesis. We ask the question of whether being a tech-giant entrant reduces its likelihood of securing second-round VC funding and leads to a less successful exit. While the exact emergence of kill zone practices remains unclear, we designate the period from 2012 to 2015 as our event period due to several notable cases, including the Snap and Facebook incident in 2013. Additionally, Zhu and Liu (2018) examined Amazon's entry into the product spaces of small rivals from 2013 to 2014. We validate the appropriateness of this event period by annually assessing the kill zone effect, which is more evident from 2012 to 2015 but diminishes during 2016 to 2018.[6]

To investigate the factors contributing to the observed kill zone effects during 2012-2015, we consider three non-mutually exclusive hypotheses: the venture experimentation hypothesis, the network effect hypothesis, and the product life cycle hypothesis. According to the venture experimentation hypothesis, VCs may find it challenging to evaluate tech-giant entrants, leading them to invest smaller amounts in multiple startups as a form of "experimentation" and subsequently abandoning unsuccessful ones, which reduce the likelihood of follow-on funding (Kerr et al., 2014). We use entrants with patents to proxy for the easy of valuation because they are more tangible than those without. The network effect hypothesis posits that the value of a platform increases with more users, making it difficult for new platforms to replace established ones, resulting in a lower likelihood of receiving follow-on financing (Parker & Van Alstyne, 2005). The third hypothesis focuses on the product life cycle, where tech-giant entrants often enter emerging sectors of tech giants' businesses, but face fierce competition for follow-on funds. Our analysis reveals that, while the venture experimentation and network externality channels partially explain the observed kill zone effect in subsample tests, they do not fully account for it. Furthermore, all estimates of channel variables are significant in our baseline follow-on financing regression but their inclusions in the regression do not mitigate the kill-zone effect suggesting the robustness of our main findings.

Besides our analysis of startups, we examine from the perspective of incumbents whether overall startup entries, referred to as New Entry Threats (NET), measured at the first VC rounds, have declined for tech giants and whether their M&A activities have a deterrent effect on such entries. It is important to note that the analysis of startups is contingent upon actual startup entries and VC financing. Documenting lower probabilities of follow-on financing does not necessarily imply a decline in overall subsequent new entries, as higher potential payoffs can offset the downside of lower success probabilities. To investigate entry dynamics for incumbents over time, we analyze NET for the following two years in relation to explanatory variables. Our findings reveal that both tech and bench giants face significantly higher NET compared to the average IT firm during the event period of 2013-2015.[7] However, both giant groups experience significant declines in NET during 2016-2018 but it is less significant for tech giants in some model specifications. The level of entries remains on par with the base group even after the declines.[8] Note that NET measures new entries when startups receive their first-round VC funds, and the significantly higher NET over time suggests that tech giants have encountered a greater cumulative influx of entries compared to the average IT firm. Regarding M&A deterrence, we found no systematic evidence supporting the claim that the M&As conducted by tech giants are associated with lower entries.

Our analysis complements existing studies on the kill zone effect. While Koski et al. (2020) focus on the product market level, our study is at the individual startup level, allowing us to examine VC and startup characteristics and track startup outcomes. Kamepalli et al. (2020) investigate nine specific acquisitions by Facebook and Google and analyze VC financing for startups similar to the acquired targets. In contrast, our study is broader in scope, encompassing not only the effects of M&As but also comprehensive startup-level analyses without a clear winner. These findings provide insights for startups and VCs making entry and investment decisions.

Our paper adds to the concerns surrounding the dominance of tech giants and their impact on market structures and startups' innovation efforts. However, existing studies often have specific focuses, partly due to the complexity of tech giants' businesses. For example, besides Zhu and Liu (2018) mentioned above,

[6] See Subsection 2.1 for detailed discussions of selecting our event period.

[7] Note that Facebook went public in 2012. We can only evaluate NET from 2013 and onwards for the analyses including Facebook.

[8] For a summary of papers supporting or against the claim of severity of the kill zone effect, see the article entitled "Monopoly Myths: Is Big Tech Creating "Kill Zones"?" by Joe Kennedy, November 9, 2020, https://itif.org/publications/2020/11/09/monopoly-myths-big-tech-creating-kill-zones/ (last accessed: June 9, 2023).

Wen and Zhu (2019) examine how app developers adjust their innovative efforts in response to platform owner entries on Google's Android mobile platform. While our study is not for a specific product or tactic, it captures overall product similarities between incumbent-startup pairs. Thus, our work complements the specific studies by examining tech giants' entrants and VC investments, serving as a proxy for investments in innovations.

Our research also contributes to the literature on M&As and antitrust concerns. Acquirers often outsource R&D or restructure acquired businesses to exploit their comparative advantages (Higgins & Rodriguez, 2006; Maksimovic et al., 2011). Acquisitions of startups also facilitate the scaling up of emerging technologies in the hands of resourceful incumbents. However, Cunningham et al. (2021) document intentional killer acquisitions aimed at preventing the development of competing products in the pharmaceutical industry. Segal and Whinston (2007) highlight the tension of antitrust restrictions that the same restrictions protecting entrants can also reduce their expected profits leading to a lower level of innovation.

Lastly, our study directly speaks to the kill-zone debates prominently displayed in the workshop held by the Department of Justice and Stanford University in February 2020.[9] Our evidence of the kill zone effect during 2012-2015 aligns with the concerns expressed by proponents. However, the transient nature of the kill zone, dissipating after 2015, and the high level of startup entries inform opponents that this allegation may not be a significant concern. The channel tests partially address the questions posed by antitrust officials seeking to identify these kill zones. We demonstrate that the kill zone effect is concentrated among tech-giant entrants without patents, operating in segments characterized by high network effects.

2. Data and Variables

We use multiple sources to construct our data that are drawn heavily from Refinitiv SDC platinum (SDC hereafter) databases. We focus on the firms in the IT industries identified by 24 4-digit NAICS industry codes (Hecker 2005) and firms classified as in the high-tech industry upon their IPOs in the SDC new issues database. The high-tech IPO list captures the dynamic in high-tech industry better than existing NAICS codes. Otherwise, it would have left out giant firms like Amazon and Facebook. Financial data and firm characteristics are obtained from Compustat. We obtain M&A data of U.S. based public firms from the SDC mergers and acquisitions database. Our entry variables are variants of the NET 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 incumbents with those of entrepreneurial startups. VC and startup information is obtained from the SDC VentureXpert database. Patent data for entrants are from Google Patents. We describe the key variables in Table 1 in Appendix.

2.1 Event Period

To define our event period, we note that the kill zone allegation intensified over time and climaxed surrounding the publication of an article in the Economist (cited in footnote 2) in 2018. The Economist article reports many specific examples of how tech giants may have created the kill zone since 2013. As it takes time to have a practice to gain notice and to develop concerns, it is unclear exactly when it started. Furthermore, once a practice has raised concerns, the intense scrutiny can affect corporate behaviors. Based on these considerations, we define 2012 to 2015 as our event years. Besides, Facebook went public in 2012 as a gigantic unicorn. We end our main analysis in 2015 because it takes several years to track startup exits and second-round VC financing. We follow startups until March 13, 2023.

2.2 Defining the Startups' Entries and Measuring Incumbents' New Entry Threats

We adopt the measure of incumbents' new entry threats (NET) from a text mining technique introduced by Pan et al. (2019) (we refer as NET-alt). They measure overall threats from startup new entries using the cosine similarity between the product description of an incumbent firm and the aggregated product descriptions from startups that received initial stage VC funding. The cosine similarity-based NET measure is bounded between 0 and 100 after scaling by 100. Higher values represent greater similarity between startups and incumbents.

Different from Pan et al. (2019), we need pairwise similarity scores between each incumbent and each startup to define the startup's entry zone. To capture

[9] For the kill-zone panel discussions, visit https://www.justice.gov/atr/events/public-workshop-venture-capital-and-antitrust (last accessed: June 7, 2023). For a summary of key comments from the workshop, see the article titled "DOJ lawyers ask startup investors about big tech's 'kill zones'", https://www.protocol.com/doj-antitrust-venture-capital-workshop (last accessed: June 7, 2023).

meaningful entries, we only consider startups in the IT sector, which VentureXpert denotes as "Information Technology" in item "Company Industry Class." Each year, we code entry equals one if the similarity score between a pair of startup and incumbent is above the 90th percentile of all scores of that year. If a startup has made an entry in any of the tech-giants' product spaces, we consider it enters tech-giant zone. We define entries into bench-giant zone similarly. Furthermore, for each incumbent, we aggregate the entry dummies and scale it by total available scores during the same year (referred as NET). Therefore, it is consistent with our startup entry measures based on the 90th percentile threshold.

2.3 Tech Giants and Benchmark Giants

There is no clear rule as to how one can classify tech giants. We take the obvious approach and define Amazon, Apple, Facebook, Google, and Microsoft as tech giants because they are the focus of recent antitrust investigations and are alleged to engage in kill zone behaviors. To ensure that we include the other largest tech firms as benchmarks, 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 keep fourteen firms that have market capitalization above $100 billion in 2018. The top five companies are our tech-giant sample. We choose five other companies from the remaining nine as the benchmark giants based on the closeness of startup entrants' business segments, which are in item "Company Industry Sub-Group 3" from VentureXpert. This should provide a better control of similar business opportunities. Adobe, Cisco, Salesforce.com, IBM, and Oracle are closer to tech giants in terms of their startup entrants' business segments than Visa, Verizon, Intel, and AT&T are. Therefore, we use the former five tech firms as benchmark giants. Our main conclusions remain robust if we use alternative list of benchmark giants. Besides comparing tech giants to five benchmark giants, we use firms in IT industries as an additional base comparison group.

2.4 Other Variables

Characteristics of VC Financing and Exits. For each startup in our sample, we identify the VC firms that provide the first-round seed or early-stage financing. We calculate two VC reputation and experience variables—one for near term, i.e., VC firm round counts within the prior three calendar years, and one for longer term, i.e., VC firm age. We follow our sample startups until the March 13, 2023 in VentureXpert database and identify their exit types as IPO, merger, and defunct.

Channel test Variables. To test the venture experimentation hypothesis, we use whether a startup filed patents prior to its first VC round as a proxy of asset tangibility. We construct a network effect variable based on startup entries at the industry level. We follow Srinivasan et al. (2004) to assign specific network-effects scores to 4-digit NAICS industries, which is then mapped to primary SIC codes. For the product life cycle hypothesis, we construct a sector growth variable and a fund competitiveness variable. They are defined in Table 1 in Appendix.

Incumbents' M&As and Other Explanatory Variables. For the incumbent analysis, our key explanatory variable is the number of M&A activities. We also include several key variables that can affect new entry decisions, such as product similarity (PMC) developed by Hoberg and Phillips (2016), R&D and capital investments, etc. The summary statistics and sample distribution by year are available upon request due to the page limitation.

3. Empirical Design and Findings

3.1 Startup Second-Round VC Financing

The kill zone allegation centers on the observation that VCs' willingness to fund tech-giant entrants. Our analysis starts from the likelihood of startups receiving second-round financing given that they have successfully received the first-round financing. We first conduct yearly comparisons of tech-giant entrants versus bench-giant entrants to verify the appropriateness of our event period. Table 2 reports the yearly logit regressions analyzing the likelihood of second-round VC financing from 2010 to 2018. For brevity, we only report the coefficients and z-statistics for "Giant-Entrant"[10] and "Bench-Entrant" and the test of difference between them each year, but all control variables in equation (1) are included in the regression models. There are no statistical differences between these two types of entrants from 2010 to 2011.

Year 2012 appears to be a transition year when the test of differences between these two types of entrants is significant. The magnitude and significance of estimates increase from 2013 to 2015. The results are consistent with the kill zone hypothesis. Nonetheless, the effect appears to be transitory, all coefficients from 2016 to

[10] The terms "Giant-Entrant" and "Bench-Entrant" are explicitly defined in Table 1 of the Appendix. It's important to note that despite some overlap between the entries of tech giants and bench giants, a significant number of startups are uniquely associated with one of the two categories. Such clear distinctions allow us to observe the varying behaviors of startups from each group.

2018 are insignificantly different from zero, which is consistent with the claim that tech giants can change behaviors when they are under intense scrutiny by the authorities and the media. It further strengthens the allegation of kill zone effect and justifies our choice of event period described in Subsection 2.1.

Table 2 Yearly logit regressions of startup second-round VC financing likelihood

	=1 if Giant-Entrant		=1 if Bench-Entrant		Test of Giant-Entrant = Bench-Entrant			
Year	(1) Coef.	(2) z	(3) Coef.	(4) z	(5) Chi^2	(6) P-value	Obs.	pseudo-R^2
Panel A: Without Facebook								
2010	0.45*	[1.80]	0.02	[0.08]	1.07	0.30	450	0.07
2011	0.04	[0.21]	0.30	[1.50]	0.59	0.44	662	0.08
2012	-0.15	[-0.75]	0.39**	[1.97]	2.65	0.10	632	0.09
2013	-0.50**	[-2.51]	0.33*	[1.66]	5.83	0.02	690	0.10
2014	-0.23	[-1.28]	0.30	[1.64]	2.93	0.09	885	0.10
2015	-0.37**	[-2.05]	0.36**	[2.00]	5.22	0.02	958	0.11
2016	-0.03	[-0.15]	0.11	[0.58]	0.18	0.67	839	0.07
2017	-0.03	[-0.16]	0.29	[1.62]	1.05	0.31	917	0.06
2018	0.19	[1.08]	-0.13	[-0.70]	1.00	0.32	872	0.04

*, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, for a two-tailed test. The baseline group is the startups with no business overlap with either Tech Giants or Bench Giants.

In Table 3, we test the changes in kill zone effects across periods using equation (1) as follow:

$$Y_i = \alpha + \beta_1 \text{Giant-Entrant}_i + \beta_2 \text{Bench-Entrant}_i + \beta_3 \text{Giant-Entrant}_i \text{ X } \text{Post}_i + \beta_4 \text{Bench-Entrant}_i \times \text{Post}_i + \beta_5 \text{Post}_i + \delta' X_i + \varepsilon_i \quad (1)$$

where "Post" is a dummy variable that equals to one if round year of a startup is after 2011, and 0 otherwise. "Giant-Entrant" and "Bench-Entrant" and their interactions with "Post" are the key explanatory variables that we use to compare the startups entering different product zone surrounding 2012, the starting of the event period Tech-giant entrants experience a significant decline in the likelihood of receiving second-round VC financing as reported in column (1) of Table 3. In terms of economic significance, being a tech-giant's entrant reduces the probability of second-round financing by 7% across periods as indicated in column (2). In contrast to that of benchmark entrants gaining 5.7 %, the net effect is nearly 13%. These results show that the kill zone allegation is not without merit and requires thorough investigations.

In column (3) of Table 3, we include several channel test variables. We find that fund competitiveness (sector growth) significantly reduces (increases) the likelihood of receiving second-round financing. Surprisingly, the estimated coefficient on network effect score is significantly positive as theory proposed by Kamepalli et al. (2020) predicts that kill-zone effect should be stronger in high network sectors. Entrants with broader entries are significantly more likely to obtain second-round financing. If these variables are the main reasons driving the observed kill-zone effects, the inclusion of them should reduce the magnitude and significance of estimates on tech- and bench-giant entrants during 2012-2015. However, they both remain significant, and the magnitudes are similar. Among the control variables, both first-round amounts and startup age show significant and consistent estimates across different model specification. Larger first-round amounts and younger startups have significantly higher likelihood of receiving second-round VC funds. However, first-round VC reputation, VC experience, and the size of VC syndicate have no significant effects on subsequent financing likelihood.[11]

Table 3 Logit regressions of second-round VC financing surrounding 2012[12]

VARIABLES	(1) Coeff	(2) ME	(3) Coeff	(4) ME
Entry-Giant	0.07	0.013	0.02	0.005
	[0.77]	[0.768]	[0.26]	[0.258]
Entry-Bench	0.09	0.018	-0.02	-0.004
	[1.06]	[1.057]	[-0.21]	[-0.208]
Entry-Giant × post	-0.37***	-0.070***	-0.40***	-0.075***
	[-2.87]	[-2.872]	[-3.07]	[-3.077]
Entry-Bench × post	0.30**	0.057**	0.27**	0.051**
	[2.33]	[2.337]	[2.09]	[2.088]
=1 if post 2012	-0.66***	-0.126***	-0.74***	-0.141***
	[-4.06]	[-4.076]	[-4.39]	[-4.409]
Breadth of Entry			0.07**	0.013**
			[2.32]	[2.327]
Fund Competitiveness			-0.27*	-0.052*
			[-1.79]	[-1.789]
Sector Growth			0.79***	0.150***
			[4.30]	[4.316]
Network Effect Score			0.02***	0.004***
			[3.18]	[3.191]
Startup level controls	Yes	Yes	Yes	Yes

[11] For brevity, the coefficients of control variables are omitted in the main paper; however, the complete table can be provided upon request.

[12] Because Facebook went public in 2012, this analysis cannot include Facebook. To ensure data consistency, we only use four tech giants and four benchmark giants.

Obs	6,555	6,555	6,550	6,550
pseudo-R	0.08		0.09	

*, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, for a two-tailed test. The baseline group is the startups with no business overlap with either Tech Giants or Bench Giants.

3.2 Channel Tests using Subsamples

To investigate the sources of kill-zone effects, we conduct subsample tests and include patent information focusing on the startups that are either entrants of tech giants or bench giants during 2012-2015.[13] The subsample test (reported in Table 4 in Appendix) shows that the kill zone effect is concentrated among tech-giant entrants without patents, which lend support for the venture experimentation hypothesis but only partially.

In Table 4, we also conduct subsample tests of other channels split by the median of variables of interests, which includes first-round amounts, VC reputation, entry strategy breadth, fund competitiveness, sector growth, and network effects. All the tests of differences between giant entrant groups are significant, except for the subsample of entrants in the low network effect sectors. The difference in coefficients between tech-giant and bench-giant entrants for low network effect sector is -0.23 (-0.36-(-0.13)), that for high network effect sector is -1.04 (-0.72-0.32). The results suggest that, among these channel test variables, only network effect can partially explain the kill-zone effect. Note that in Table 3, including network effect score as an explanatory variable does not reduce the magnitude and significance of estimated coefficients related to the kill zone effect. Therefore, we did not find evidence supporting the product life cycle hypothesis but some evidence of the network effect score hypothesis through the subsample tests.

3.3 Startup Exits

We now turn to the exit analyses and examine whether tech-giant entrants experience a lower successful exit likelihood. We use the sample period from 2012 to 2015, which gives us about seven years to follow the outcomes of last startup vintage. The findings on exits as reported in Table 5 support the kill zone hypothesis. Relative to bench-giant entrants, tech-giant entrants experience a significant increase in the likelihood of being defunct or inactive (defunct hereafter). The results are not only highly statistically significant but also economically meaningful. The marginal effect from estimates in table 5 shows that, relative to the base IT entrants, being a tech-giant entrant increases the probability of being defunct by 9.1%, while the corresponding number for bench-giant entrants is -5%. Therefore, the net effect for being defunct is 14.1%. There are no differences in terms of the likelihood of conducting IPO or being acquired between tech- and bench-giant entrants.

First-round amounts are significantly positively associated with successful exits and reduce the chance of startups being defunct. Older startups have a significantly higher chance of being defunct. The estimated coefficients on "Breadth of entry" show that startups adopting a broader entry strategy have a significantly lower probability of being defunct. Fund competitiveness has no significant effects on exits but sector growth significantly decreases the chance of being defunct. Startups in the high network effect sector has significantly higher likelihood of being acquired. Overall, our findings lend support to the kill zone hypothesis. Evidence consistent with this claim includes tech-giant entrants experience significant declines in the likelihood of second-round VC financing and have a significantly higher likelihood of being defunct or inactive. Including the proxies for channel tests does not explain away the significance of kill zone effects.

Table 5 The likelihood of exit by type: multinomial logit regressions

	Coefficients		
	(1)	(2)	(3)
Exit Type:	IPO	MA	Defunct
Entry-Giant	0.001	0.13	0.57***
	[0.00]	[1.13]	[5.04]
Entry-Bench	-0.80**	0.06	-0.29**
	[-2.10]	[0.45]	[-2.26]
Breadth of Entry	0.04	-0.03	-0.17***
	[0.29]	[-0.64]	[-3.81]
Fund Competitiveness	0.49	0.05	0.17
	[0.64]	[0.19]	[0.64]
Sector Growth	1.17	0.18	-0.74**
	[1.49]	[0.61]	[-2.44]
Network Effect Score	-0.01	0.04***	-0.00
	[-0.19]	[3.61]	[-0.28]
Startup Level Controls	Yes	Yes	Yes
Obs	3,262		
pseudo-R	0.0945		
Chi^2	2.328	0.154	21.84

[13] In the comprehensive analysis conducted on a sample of all giant startups, irrespective of whether they hold patents, it was found that patents filed prior to the first round of funding have a statistically significant positive impact on subsequent funding. However, despite this positive effect, there is still a notable decrease in the likelihood of obtaining second follow-up funding for Tech Giant entrants. As a result, we can only conclude that the venture experimentation hypothesis is partially supported. References available upon request.

P-value	0.127	0.695	0

*, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, for a two-tailed test. The baseline group is the startups with no business overlap with either Tech Giants or Bench Giants.

3.4 Incumbents' New Entry Threats (NET) and M&As

In the previous subsection, we document evidence for the kill zone hypothesis using startups' second-round financing likelihood and exit outcomes. A more pertinent question is whether the kill zone effect pervasively discourages entrepreneurship and innovation, to the point that new startup entries have dropped significantly to a level that raises concerns. Therefore, we conduct a set of analysis from the perspective of incumbents to investigate this question. We extend our empirical tests based on the following two questions: (1) whether tech giants experience higher new entry threats than bench giants surrounding 2015; (2) whether tech-giants' M&A activities produce more deterrent effects than other bench giants.

Table 6 New Entry Threat (NET): random effects panel regressions

t+1:	2013-2015 vs. 2016-2018			
Dependent Variable:	NET	NET	NET-alt	NET-alt
	(1)	(2)	(3)	(4)
	t+1	t+2	t+1	t+2
=1 if Giant	8.00*	9.15*	7.65***	7.68***
	[1.92]	[1.91]	[2.68]	[2.82]
Giant × M&A Deal Count	0.06	-0.22	-0.02	-0.19**
	[0.69]	[-1.22]	[-0.29]	[-2.22]
Giant × Post	-2.87	-3.07	-4.40*	-4.35**
	[-0.92]	[-1.04]	[-1.81]	[-2.07]
Giant × M&A × Post	-0.10	0.10	0.06	0.23*
	[-0.75]	[0.68]	[0.51]	[1.85]
=1 if Benchmark	9.64**	7.77*	7.25**	6.32**
	[2.30]	[1.81]	[2.52]	[2.32]
Bench × M&A Deal Count	-0.19	-0.26**	-0.21***	-0.28***
	[-1.20]	[-2.07]	[-3.44]	[-4.01]
Bench × Post	-6.87***	-5.14**	-3.93***	-2.82***
	[-4.03]	[-1.96]	[-5.29]	[-3.81]
Bench × M&A × Post	0.43***	0.37	0.24***	0.23***
	[2.74]	[1.55]	[3.02]	[3.09]
=1 if post 2015	-0.15	-0.13	-0.28***	0.02
	[-0.88]	[-0.85]	[-3.12]	[0.25]
Incumbent Level Controls	Yes	Yes	Yes	Yes
Obs	4,691	3,653	4,713	3,737
# of firms	1,068	964	1,076	971
R^2-Overall	0.203	0.200	0.251	0.249

*, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, for a two-tailed test.

We use random effects panel regressions with clustered standard errors allowing correlation within incumbents.[14] Table 6 reports the results of NET for the next two years following the time we measure explanatory variables. We use two different NET measures. The first one aggregates the entry indicator based on the pairwise similarity score between each incumbent and each startup that passes the threshold of yearly 90th percentile (columns 1 and 2). The second one (labeled as NET-alt) is from Pan et al. (2019). They first aggregate all startup business descriptions each year and use this aggregated document to calculate a similarity score with each incumbent. As Table 6 shows, both measures produce consistent results.

We find that the NET of both types of giants are significantly higher than that of base IT firms during our event period (2012-2015), but it declines for both types of giants later. However, the declines are more significant among bench giants. Taken together, the kill zone effect does not appear to be pervasive because the new startup entries of tech giants remain at a level comparable to other incumbents in the technology sectors and there is no systematic entry deterrence effect by tech-giant M&As.

Note that NET only counts each startup entry once when it receives first-round VC funds. If we accumulate such entries, it suggests that tech giants are facing much higher entry pressures than an average IT firm. In sum, our study documents evidence that kill zone exits and new startup entries for tech giants have declined but only to a level that is comparable to other IT firms. This is because tech giants have a significantly higher NET in the first place. One plausible explanation for the observed entry patterns could be that, despite the lower probability of success, if the payoff given success is high enough, creative entrepreneurs will still be willing to innovate and be able to attract VC supports. To explore this possibility, we examined our raw data. Among the M&A deals that we were able to match startup information as targets and obtain transaction values, the mean deal value for giant targets is \$1.75 billion, while it is \$197.89 million for other IT firms. Additionally, the corresponding average first-round VC investment amount is \$15.375 million for giant targets

[14] We cannot use fixed effects models because the classification of tech giants and bench giants are constant.

and $7.52 million for other IT firms. The significantly higher payoffs can potentially offset the downside of a smaller probability of success.

4. Conclusions

In this paper, we evaluate the concerns regarding the alleged kill zone instigated by tech giants' anticompetitive tactics within a holistic framework. By employing a pairwise business similarity score between a startup and an incumbent, we can identify entrants more effectively than through traditional industry classifications. While our approach does not focus on a specific anticompetitive strategy or product market, it is crucial for understanding the overall impacts on startups and VC investments. Additionally, we explore three potential channels that may contribute to the occurrence of this kill-zone phenomenon.

Through our innovative approach, we provide evidence of significant declines (increases) in the probabilities of second-round VC funding (being defunct) among tech-giant entrants compared to bench-giant entrants. Regarding the channels that give rise to kill-zone effects, we identify two factors—asset tangibility and network effect—that help to explain these effects. However, we find that tech giants have a considerably higher number of new entries in the first place compared to an average IT firm, and there is no evidence that their M&A activities deter new entries.

Taken together, our paper demonstrates that despite the alleged anti-competitive tactics employed by tech giants to restrict market entry, the NETs of tech giants are comparable to those of bench giants and the average IT firm. Furthermore, the kill-zone effect appears to be temporary and dissipates during the period of 2016-2018, even among closer entrants. Nevertheless, we cannot dismiss the possibility that the decline of kill effects is influenced by media coverage and regulatory attention. It is important to note that the strength of the kill-zone effect may increase in the future and warrants ongoing monitoring once public scrutiny starts to wane. We believe that the analytical framework employed in this study offers a sensible approach for such monitoring purposes.

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Appendix

Table 1 Key variable definitions

Variable Names	Variable Definitions
Startup Variables	
=1 if Giant-Entrant	A dummy variable that equals one if a startup has a product similarity score with a tech giant that is above or equals the 90th percentile of a yearly sample, and 0 otherwise.
=1 if Bench-Entrant	A dummy variable that equals one if a startup has a product similarity score with a bench giant above or equals the 90th percentile of a yearly sample, and 0 otherwise.
Fund Competitiveness	An industry level variable that measures the follow-on funding availability of a startup's business segment based on item "Company Industry Sub-Group 3" from VentureXpert. The variable is calculated by aggregating the number of seed/early stage VC deals in a startup's business segment during 3 years surrounding the first round year, i.e., year [-1, 1], divide by the total number of later stage VC deals in a higher level business segment, i.e., item "Company Industry Sub-Group 2" from VentureXpert during the same period.
Sector Growth	An industry level variable that measures a startup's business segment growth based on item "Company Industry Sub-Group 3" from VentureXpert. The variable is calculated by aggregating the number of seed/early stage VC deals in a startup's business segment during the first round year divide by its 5-year average during years [-4, 0], i.e., from prior four years to the first round year.
Network Effect Score	A continuous variable that measures the extent of network effect of a startup's four-digit primary SIC industry, which is mapped into NAICS industry with a network-effect score designated based on Srinivasan, Lilien, and Rangaswamy (2004).
Breadth of Entry	Natural log of one plus total number of incumbents' product spaces that a startup has entered during 1st round year.
=1 if Have Patents	A dummy variable that equals to one if a startup has patents available in Google Patents.
No. of Patents	Total number of patents available in Google Patents.
Ln(Patents-Filing)	Natural log of one plus number of patents filed before 1st round.
Ln(Round Amounts)	Natural log of one plus total real dollar amounts (in 2012 dollar) of VC financing for a round in thousands. If the disclosed amounts are not available, estimated amounts are used.
Ln(No. of VCs)	Natural log of one plus number of VC firms participating in a round.
Ln(VC Deals)	Natural log of one plus total number of deals a VC firm participated in the previous three years. For a round where more than one VC participated, the VC with the largest deal counts is used.
Ln(VC Age)	Natural log of one plus VC firm age. For a round where more than one VC participated, the oldest VC is used.
Ln(Startup Age)	Natural log of one plus startup firm age
=1 if Next Round	A dummy variable that equals one if a startup has received the next round before the end of October 2020, and 0 otherwise.
Ln(Days to Next Round)	Natural log of one plus number of days to next round
=1 if post 2012 (2016)	A dummy variable that equals to one if round year of a startup is after 2011 (2015), and 0 otherwise. For the analysis of incumbents, fiscal year is used.

Table 4 Logit Regressions of Second-Round VC Financing by Subsample

This table reports the likelihood of second-round VC financing using a sample of startups' first-round years from 2012 to 2015. The samples in the subsample category of "Patents Filing" only include tech giant and bench giant entrants. The dependent variable equals one if a startup has second-round financing prior to March 2023, and 0 otherwise. Columns (1) and (2) report estimated coefficients (Coef.) and z-statistics (z) for the dummy variable indicating tech-giant entrants, columns (3) and (4) report those indicating bench-giant entrants. Other variables used in column (3) of Table 4 are included but not reported for brevity. Tests of differences in coefficients between tech- and bench-giant entrants are reported in columns (5) and (6). Subsamples are split using the median value of each variable listed beneath the column "Subsample Category." See Table 1 for key variable definitions. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, for a two-tailed test.

Subsample Category		=1 if Giant-Entrant		=1 if Bench-Entrant		Test of Giant-Entrant = Bench-Entrant			
		(1) Coef.	(2) z	(3) Coef.	(4) z	(5) Chi2	(6) P-value	Obs.	pseudo-R^2
1st Round Amount	Low	-0.54***	[-3.98]	0.11	[0.71]	8.76	0.00	1,635	0.10
	High	-0.65***	[-4.30]	0.23	[1.38]	13.15	0.00	1,616	0.07
VC Reputation	Low	-0.65***	[-4.08]	0.18	[1.01]	10.14	0.00	1,414	0.15
	High	-0.47***	[-3.58]	0.14	[0.93]	8.37	0.00	1,848	0.07
Breadth of Entry	Low	-0.57***	[-4.17]	0.25	[1.40]	11.64	0.00	1,633	0.11
	High	-0.53***	[-3.53]	0.07	[0.42]	6.56	0.01	1,629	0.10
Fund Competitiveness	Low	-0.60***	[-4.18]	0.25	[1.58]	12.81	0.00	1,634	0.12
	High	-0.54***	[-3.76]	0.09	[0.59]	8.05	0.00	1,628	0.10
Sector Growth	Low	-0.56***	[-3.98]	0.04	[0.24]	6.96	0.01	1,518	0.10
	High	-0.62***	[-4.26]	0.29*	[1.76]	14.89	0.00	1,744	0.12
Network Effect Score	Low	-0.36**	[-2.07]	-0.13	[-0.71]	0.67	0.41	1,142	0.10
	High	-0.72***	[-5.62]	0.32**	[2.24]	25.23	0.00	2,120	0.12
Patents Filing	No	-0.68***	[-3.99]					1,502	0.09
	Yes	-0.52	[-1.25]					437	0.11