Post-M&A Performance in Mobile App Developing Startups

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ABSTRACT

M&A is becoming increasingly common as a key growth and exit mechanism for startups. However, it is still a relatively undocumented phenomenon, due to the challenges of tracking target-specific metrics once the target and acquirer have merged. Using app ranking as a proxy for target performance, I manage to quantify the effects of acquisition on a target's growth post-acquisition. Firstly, we find that mobile app developing startups generally experience significant, positive, and rapid benefits in ranking from being acquired. Secondly, our observations about startups' positive growth trajectories allow us to make inferences about circumstances where the increased access to resources afforded by an acquisition is particularly valuable in accelerating the target's growth. Finally, we observe some interesting exceptions where targets' apps experience rapid declines in ranking post-acquisition, providing empirical evidence for the important roles that startup acquisitions can also play in non-product-related functions, such as acquiring talent or reducing competition.

Keywords: mobile apps, mergers, acquisitions, startups, survival, Crunchbase, innovation, entrepreneurship, app ranking, Mobile Innovation Group, App Store

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1. INTRODUCTION

Just as all parties must come to an end, all startups must eventually exit. For a surviving company, the exit choice typically comes down to one of two options - go public, or be acquired by another company. The vast majority of startups end up getting acquired by another company: in 2015, the National Venture Capital Association (NVCA) reported 884 exits of VC-backed companies by a merger or acquisition (M&A) transaction, compared to 77 VC-backed IPOs, suggesting that a startup is >10x more likely to be acquired than go public.

Despite all this, M&A in startups is still a relatively poorly-documented phenomenon, having taken a backseat to its sexier counterpart: the IPO. We know very little about what happens to acquired startups after these acquisitions close – how do they perform as part of a merged firm? We know even less about what drives post-acquisition performance – what factors, if any, make an acquirer's resources particularly valuable to the target? Finally, we do not have strong frameworks for understanding the unique reasons why acquisitions of startups happen – why might a traditional company to acquire a startup rather than a more mature company?

This paper aims to plug our knowledge gap in the economics of startup M&A by studying and documenting emerging trends in post-acquisition performance of startups, and understanding why, if at all, these trends differ from their counterparts arising from acquisitions in traditional industries. In this project, I propose a novel method of tracking post-acquisition target performance by using mobile apps' rankings as a proxy for their developers' performance and growth. By using a massive dataset tracking the daily rankings of the top 500 free and paid apps in the iTunes App Store, we can quantify trends about the magnitude, direction, and speed of acquisition-related effects in mobile app developing startups. As a corollary, we can also observe and define the specific effects of various deal characteristics (e.g. acquirer age, market overlap, geographical proximity, etc.) on post-acquisition performance, allowing us to draw interesting inferences about circumstances where the acquirer's resources are of particular value in boosting the commercial value of the target's products. Furthermore, observing the flipside of these circumstances – cases where the benefits from acquisition do not materialize as expected in the target's products – also provides us with empirical evidence for other motivations of startup acquisitions, where the target's products may not be the main attraction for the acquirer.

Industry Background

In the late 2000s and early 2010s, the ubiquity of mobile technology and smartphones fueled a resurgence in the number of startups formed in Silicon Valley. Drawn towards the new era of mobile smart devices, many of these new ventures decided to focus on mobile app development rather than the web-based ventures that had dominated the previous dot-com boom. Firstly, barriers to entry were low – the prevalence of app-developing tools and the relative ease of app development made it easy for part-time technologists or less-seasoned professionals to try their hand at app development during their spare time. In 2012, almost 250,000 independent individuals were registered as app developers for the iTunes App Store, and more than 270,000 independent individuals published on the Android App Store (Ford, 2013). Secondly, the market opportunity was huge - more than 60 million Americans reported owning a smartphone in 2012 (Gartner Research, 2012), and that number has since climbed to more than 230 million, or approximately 77% of the population, in 2017 (Pew Research Center, 2017). The University of Maryland estimated that app developing companies and individuals represented more than 180,000 jobs, and added $12B to the US economy in 2011 (University of Maryland, 2011).

Mobile app developing companies attracted 10% of the total invested capital from venture capital firms (Wortham, 2012), and high-profile app exits like Facebook's 2012 acquisition of Instagram for $1B only served to heighten the mobile app development frenzy.

In July 2008, Apple launched the iTunes App Store, a platform for developers to publish their own apps for the iPhone. At the time, it had 552 apps available, of which 135 were offered for free. By March of 2012, there were more than 550,000 apps in the App Store, with a total of 25 billion downloads worldwide (Apple, 2012). By 2016, the App Store featured more than 2.2 million apps in total, and app developers had collectively earned a total of $20B from app revenues. However, as the App Store grew, app discovery became increasingly challenging, and therefore Apple started publishing lists of top-ranked apps each day. There are three main top lists: top free apps, top grossing apps, and top paid apps. In this paper, I have focused only on the top free and top paid lists, as apps on these lists are mutually exclusive.[1] Apple does not release its methodology for ranking these apps; however, industry interviews suggest that the main determining factor is the number of downloads each app has.

App ranking is therefore an interesting proxy for developer performance. In a crowded ecosystem like the iTunes App Store, consumers rely almost exclusively on aggregated data like ratings and rankings to help them determine which apps they should purchase or download (Hao *et al*, 2011; Arment, 2013; Walz, 2015), reinforcing what some critics have called a "vicious cycle of downloads" – apps on the top lists are more likely to get downloaded, thereby maintaining their presence on the top lists. Furthermore, most of the companies I studied were small developers, and their mobile app offerings were often their sole or major product –

[1] Apps on the top grossing list may also be found on the top free or top paid lists. At a high level, top grossing lists apps which generate the most revenue – be it from paid downloads or in-app purchases. Since top grossing is a conflation of the top free and top paid apps and introduces unnecessary complexity, I have chosen to exclude top grossing apps from study at this point.

implying that the performance of their apps was likely to dictate the performance of the company as a whole.

App ranking is also attractive as an indicator of developer performance because of the availability of a large, comprehensive dataset – the Mobile Innovation Group (MIG), a consortium of researchers from various institutions focusing on the study of mobile platforms and entrepreneurship, collected a massive dataset listing the 500 apps on the top free, top grossing, and top paid lists each day from February 2010 to March 2015. I used this list to track the trajectory of top app rankings over time, giving us an objective and quantifiable measure of pre- and post-acquisition performance. Although this dataset is admittedly top-biased (we do not have specific ranking data for less-successful apps that never made it into the top 500), the less-successful apps are also unlikely acquisition targets and therefore, less interesting to us for the purposes of this study (Walz, 2015). More on the exact dataset preparation will come later on in the data and methodology sections, but the motivations of using app ranking as a proxy for developer performance should be abundantly clear to the reader at this point.

2. LITERATURE REVIEW

There is a rich body of academic literature concerning acquisitions in traditional industries, and a burgeoning academic interest in startups, especially as the field matures. That said, little research has been done specifically on acquisitions in startups, let alone on acquisitions in mobile app developing startups. However, the body of research on acquisitions in traditional industries has been instrumental in helping us come up with hypotheses on what sort of factors might play a part in generating positive gains in trade from acquisitions amongst mobile app developing companies. I will now briefly summarize the existing literature, which I have divided into two main categories: research on mobile app developing startups, and research on acquisitions in traditional industries.

Mobile app developing startups

Mobile apps are a relatively young category, having only emerged and come to prominence in the late 2000s. Most of the literature explores how standalone app developers can create "killer apps" – apps ranked at the top of their respective App Stores – and what sort of factors throughout the innovation process predispose an app towards success (Yin, David, and Chhabra, 2014; Lee and Raghu, 2014; Hallen, Davis, and Yin, 2017). Another area of study in the mobile app ecosystem is how apps can influence user behavior via various business models or user engagement (Ford, 2013; Dinner, Heerde, and Neslin; 2015).

However, the lifecycle of an app developing startup does not end with the development or even the commercialization of a product. Many of these startups are backed by venture capital firms, which ultimately force the hand of a startup in exiting within a certain period (typically within the limited life of a venture fund). Most startup exits fall into one of three categories: (1)

an initial public offering of the company's shares (IPO); (2) a sale of the company to another firm (M&A); or (3) dissolution and liquidation of the company (Broughman and Fried, 2013). Bayar and Chemmanur have examined the exit choice faced by entrepreneurs in a theoretical two-stage model, which suggests that acquisitions are more likely to occur in highly concentrated industries, where the benefits of being acquired by larger, more established firms are greater; and also that startups backed by VC firms with long-term investment horizons are more likely to be acquired than go public (2011). Data from the 2016 National Venture Capital Association (NVCA) yearbook in Table 1 below empirically supports Bayar and Chemmanur's findings with respect to VC-backed startups, and the data below also suggests that the popularity of IPOs as an exit mechanism has fallen in recent years.

Table 1: IPO and M&A exits of VC-backed startups by year

	2012	2013	2014	2015	2016
IPO exits	60 *(7.0%)*	89 *(10.1%)*	122 *(11.7%)*	77 *(8.0%)*	39 *(5.4%)*
Average IPO value ($M)	$2,206.8	$628.7	$437.7	$551.5	$412.3
M&A exits	799 *(93.0%)*	796 *(89.9%)*	918 *(88.3%)*	884 *(92.0%)*	687 *(94.6%)*
Average M&A value ($M)	$128.9	$109.8	$239.7	$164.0	$248.0

Acquisitions in traditional industries

It is a well-accepted fact that different types of acquirers may result in different post-acquisition performance outcomes. For instance, it is widely accepted as common knowledge in the industry that financial acquirers (i.e. private equity firms) often pay lower prices for acquisitions than strategic acquirers (loosely defined as operating companies that operate in the same, or similar, industry as the target), as the latter can theoretically realize revenue and/or cost synergies from the acquisition (Martos-Vila *et al*, 2013).

However, there are a few issues with the outstanding body of work on acquisitions – most of it applies to firms in traditional, mature industries like consumer goods or healthcare, but the high-technology startup industry, characterized by "high turbulence" and "high inter-period uncertainty" (Cloodt, Hagedoorn, and Van Kranenburg, 2006) can often seem like an entire different animal with potentially different realized outcomes. Furthermore, due to the inherent difficulties of tracking target performance post-acquisition, most of these studies have focused on the value created by the acquisition for the buyer, rather than the seller. The seller is assumed to be out of the picture as soon as the transaction closes, and in most traditional industries, thisi s a reasonable assumption since M&A is typically associated with abnormally high turnover rates in the target's top management and their employees within 4 years of the transaction closing (Walsh, 1989; O'Shaughnessy, Flanagan, 1998; Sudarsanam, Mahate, 2006). Again, this is less often true in high-technology startup acquisitions. For example, consider the "acquihire" phenomenon: an acquihire is a novel Silicon Valley transaction where large firms acquire smaller startups primarily for the technical skills of the startup team, rather than the startup's product offering (Sawicki, 2015). More generally, according to anecdotal evidence from industry interviews, employee retention clauses are a major part of any M&A agreement in Silicon Valley, with employee options, salaries, and earnouts all baked into the agreed-upon sticker price for the target (First Round Capital, 2015). Hence, the main aim of this subsection is to take existing literature about M&A outcomes in traditional industries, and synthesize the body of academic knowledge contained therein with the large cache of anecdotal knowledge that has been passed on by word-of-mouth and informal advice via mentors, early investors, and accelerator programs in the startup community (Hathaway, 2016; Feld, 2012) – highlighting similarities and differences alike for potential areas of study.

Industrial specialization

The question of whether horizontal M&A (an M&A event occurring between firms operating in the same industry) or diversifying M&A (an M&A event occurring between firms in different industries) is beneficial to acquirers has been a hotly-debated one. Both points-of-view have come in and out of vogue; during the conglomerate merger wave of the 1960s (Matsusaka, 1993), companies actively sought to diversify their business activities by buying other firms operating in unrelated industries, replacing the earlier horizontal merger wave of the early 20th century. Recently, consolidation mergers have become popular once more, and acquirers usually justify M&A of this sort by citing the reduced costs of doing business and increased revenue from greater market share achievable as a result of economies of scale (Lam, 2016).

The industry in which the acquirer is operating may also play a part in determining whether diversification or consolidation M&A is more effective in increasing shareholder value. In more traditional industries (e.g. financial services; manufacturing, etc.), cross-product diversification M&A seems to have resulted in a positive and significant market reaction, and thereby increase in shareholder value for the acquirer (Lepetit, Patry & Rous, 2006; Matsusaka, 1993). However, in more technology-centric industries (e.g. biotechnology, software, etc.), researchers have found that complementary scientific knowledge and relatedness of technologies between the target and acquirer are positively correlated with post-acquisition advantages (Makri, Hitt & Lane, 2009; Al-Laham, Schweizer & Amburgey, 2009; Hussinger, 2009; Hayward, 2002). The positive gains from trade resulting from familiarity with the target and the informational advantage from working with technology like the acquirer's own seems to outweigh the loss of diversification benefits in consolidation M&A.

For the mobile app developing startups that we are considering in this paper, the high-technology context and experience seems to be a better fit. In addition, our industry interviews have also indicated that startup acquisitions have largely focused on plugging a hole in the acquirer's knowledge, or solving a specialized problem that the acquirer has not developed a solution to. Dave McClure, a partner of 500 Startups, has even gone so far as to claim that large corporations have "wholesale outsourced R&D to the startup and venture community" (CB Insights, 2017). Instead of conducting internal R&D to solve a problem faced in their normal course of business, corporations seem to find it more efficient and cost-effective to simply acquire a startup that has already been working on solving that problem for some time.

Age factors

Different organizational cultures can result in clashes during post-acquisition integration (DeVoge & Spreier, 1999; Marks, 1991; Morosini, 2004; Nahavandi & Malekzadeh, 1988; Overman, 1999; Weber & Schweiger, 1992). The age difference between a target and acquirer could be a potential predictor of the difference between organizational cultures, especially since younger startups with less rigid organizational structures are more likely to be "scrappy, lean and nimble" – all factors with which industry insiders credit their startups' success (Forbes, 2014).

On the other hand, M&A literature also suggests that general acquisition experience and knowledge is a major contributor to post-acquisition success. Experienced acquirers can better mitigate the potentially disruptive integration process, and therefore can realize larger coordination benefits than inexperienced acquirers (Al-Laham, Schweizer & Amburgey, 2009; Puranam & Srikanth, 2007; Bertrand & Betschinger, 201; Ragozzino, 2006). Age is generally correlated with acquisition experience – the older a company is, the more likely it is to have acquired companies in the past, and therefore the better it might be at navigating new M&A

processes. Furthermore, older firms are also more likely to have amassed more resources, and studies have found that having more resources available to manage the integration process has helped improve the impact of acquisitions the acquirer, even in cases where a general lack of acquisition experience might suggest otherwise (Bertrand & Betschinger, 2011).

Academic literature is conflicted about the impact of target age on acquisition – some research suggests that the younger targets are at the time of acquisition, the worse the post-acquisition performance of the combined entity will be (Ragozzino, 2006). This holds true even when the acquirer is a young entity itself. However, other studies have shown that younger targets may benefit from acquisitions earlier on in their life cycle for two main reasons: younger targets have more flexibility in their growth options, creating more opportunities for synergistic fits with the acquirer; and younger targets experience greater uncertainty in valuation, allowing the acquirer to propose a lower acquisition price (Ransbotham & Mitra, 2010).

Geography

Again, the academic literature on geographical diversification in M&A is mixed, with some studies finding negative and significant abnormal returns to acquirers in cross-border mergers (Amihud, DeLong, & Saunders, 2002; Belcher & Nail, 2001; Lepetit, Patry, & Rous, 2006; Marks, 199) due to challenges with cultural integration, a lack of specialization, and potentially incoherent corporate strategies on both ends. However, other studies have found a positive relationship between national cultural distance of the target and acquirer firms, and cross-border acquisition performance (Morosini, Shane, & Singh, 1998). Anand, Capron & Mitchell (2005) refine this assertion by claiming that the impact arising from differences in country of origin has less significance than the impact of geographical resource diversity, the latter of which outweighs the former to result in opportunities for better financial performance.

Furthermore, a strong motive for M&A is the desire to acquire customers in new regions (Selden & Colvin, 2003), which geographically diverse transactions tend to be better at.

Mobile app strategy

Finally, we turn to the question of corporate strategy decisions on acquisition outcomes. The literature on this is slightly less comprehensive than that on the previous factors, primarily due to the difficulty of identifying, describing, and quantifying corporate strategy – not to mention the uncertainty involved in subsequent implementation. In general, a strategic and organizational fit between companies was associated with improved technological performance post-acquisition (Chen, Chang & Lin, 2009; Hagedoorn & Duysters, 2010). However, while strategic complementarity helped acquirers by allowing them to use the target's existing knowledge as an input to their own processes, Puranam & Srikanth (2007) also found that this hindered their reliance on the target as an independent source of innovation. Al-Laham, Schweizer & Amburgey (2009) also found that in transactions where the acquirer was familiar with the target beforehand (i.e. they operated in the same industry, or had previously carried out partnerships together), there was an associated increase in post-acquisition patenting speed. This suggests that a continuation of corporate strategy initiated by (or existing before) the M&A transaction is generally beneficial to the combined post-transaction entity.

3. DATA

Dataset Construction

This study uses a compilation of data from many sources, some of which are publicly available online (e.g. Crunchbase and Sensor Tower), and some which was collected by the Mobile Innovation Group (MIG), a consortium of researchers at Stanford, MIT, INSEAD, and USC that studies how innovation and entrepreneurship on mobile platforms. I started with a dataset of more than 3,000 app developers who had developed apps that were, at some point between February 2010 – March 2015, on either the top free, top grossing, or top paid lists. From this developer dataset, we narrowed the list down to 434 developers that had been acquired between 2008 and 2015. Since 2008 was when the App Store launched, limiting acquisitions to a timeframe after 2008 made it more likely that the developer was acquired at least partially because of its mobile app. We identified acquired developers via a previous study on mobile apps, where research assistants working with MIG (including myself) manually investigated the characteristics of individual apps, including whether or not their developer had been acquired. For the purposes of that earlier study, an app whose developer had been acquired was referred to as an “acquired app”. I was able to leverage this pre-existing definition and derive a list of “acquired developers” from the pool of “acquired apps”, by matching the apps’ unique app IDs to their respective developers’ developer ID.

For these 434 acquired developers, I supplemented MIG’s survey of developer characteristics with acquisition-specific data from Crunchbase, containing information on the acquirer and the acquisition event itself. This eventually became the final dataset combining all the information we had on top acquired developers (henceforth known as the "acquisition characteristics dataset").

Turning now to the mobile apps themselves, I started with a comprehensive dataset collected by MIG containing the IDs of the top 500 free, grossing, and paid apps in the iTunes App Store every day between February 2010 – March 2015. Again by matching the unique app IDs to their respective developer IDs, I matched these top apps with their respective developers, and narrowed down the app ranking dataset to cover only apps created by the 434 acquired developers we studied above. I then created panel data of these apps' ranking on every single day between February 2010 – March 2015, assuming a rank of 501 if the app was not ranked (i.e. it did not manage to break into the top 500 apps) that day. Using developer ID as a key, I mapped each app to its entry in the acquisition characteristics dataset described previously. In total, 400 acquired developers were matched to corresponding top ranked apps, out of 14,186 total represented developers in the top apps.

General Summary Statistics

Tables 2-4 below summarize information on the 434 reported acquisitions of mobile app developers that occurred between February 2010 to March 2015. Note that there may be fewer than 434 observations for some characteristics – some information was not available for certain companies, which we then excluded during the regressions. A detailed explanation of each of the characteristics studied follows immediately after these tables, and may be helpful to refer to concurrently while reading these tables.

Table 2: Target Characteristics

Variable	Observations	Mean	Std. Dev.	Min	Max
Target age	424	1.856649	0.9174135	0	4.736198
Mobile only? *	434	0.294	-	-	-

Table 3: Acquirer Characteristics

Variable	Observations	Mean	Std. Dev.	Min	Max
Acquirer age	414	2.740977	1.051023	0	4.744932
Apps before acq? *	434	0.582	-	-	-
Apps after acq? *	434	0.720	-	-	-
# apps before acq	434	5.981524	15.7227	0	210
# apps after acq	434	28.78753	100.7817	0	1814

Table 4: Pairwise (deal) Characteristics

Variable	Observations	Mean	Std. Dev.	Min	Max
Age difference	406	0.8791516	1.208599	-3.367296	4.727388
Perfect market match? *	434	0.145	-	-	-
Same region? *	434	0.195	-	-	-

** Standard deviation, minimum, and maximum values are not reported for dummy variables.*

Description of variables

Target age and **acquirer age** are reported as *ln(age of company at acquisition)* in order to avoid overly biasing the samples towards companies that have been in existence for decades (e.g. large media conglomerates). Generally, companies' founding dates were publicly available online (either on Crunchbase, or via a quick search on the company's webpage). I took the year in which the company was acquired and subtracted the year in which it was founded to find the company's age in years. In the few (~20) cases where the company was founded and acquired in the same year, I manually set their age in years at acquisition to 1 to ensure that *ln(age)* would be well-defined. **Age difference** effectively represents the ratio of target age to the acquirer age, since the variables with the corresponding names refer respectively to the log of the actual age in years. Here, we see that on average, targets tended to be younger than their acquirers, but not by much – in general, there was only about a 12.1% age difference between any given target-acquirer pair.

Based on the literature surrounding company age during acquisition, I expected older acquirers to result in better deal outcomes for the target, because older acquirers tend to have more resources available at their disposal to channel towards the target. They also tend to have more acquisition experience, resulting in better target selection and more efficient integration of the target once the acquisition closes. I also expected targets involved in deals with a larger age difference between the target and acquirer to experience better outcomes, because the improvement in resource access as a percentage of the target's baseline is larger.

Mobile-only is a dummy variable that determines whether a business' offerings are offered only through its mobile app, or if it has other non-mobile offerings (e.g. brick-and-mortar stores, web-based interfaces, etc.). For example, Uber, a business that interacts with its users primarily through its app interface, would be considered a "mobile-only" company, whereas Amazon, a business that has both a mobile app and web-based offerings, would not. I determined this by going to the company's website and learning about their product offerings, and then making a judgment on whether the business could be construed as a "mobile-only" one. We determined the value of the mobile-only dummy variable only for target firms.

I expected targets that were focused on developing solely for mobile devices to do better post-acquisition compared to targets that developed for other platforms as well. I believed that developing solely for a mobile platform implied some level of specialized knowledge relative to development teams who had to spread their efforts out across a number of different platforms, and that would ultimately result in higher-quality mobile apps that could benefit disproportionately from a boost in advertising and marketing resources afforded by the acquirer.

Apps before / after acquisition were dummy variables that measured whether the acquirer had published mobile apps using its unique developer ID before / after the acquisition event occurred. This was measured only for the acquirer firms, not the targets. We excluded acquired apps (i.e. apps published under the target's unique developer ID, rather than the acquirer's) from consideration, which explains why some developers are reported as not having any apps post-acquisition despite having acquired a company with known apps. The proportion of acquirers with apps as well as the average number of apps per company increased post-acquisition – the former increasing by 13.8 percentage points, and the latter increasing by 22.806 apps, or 481%. This data was collected from Sensor Tower, an app analytics platform with some data (including number of apps per developer and their creation dates) available to the public.

I thought of the dummy variables for apps before acquisition and apps after acquisition as representative of the acquirer's knowledge base and business strategy. If an acquirer had apps before acquisition, I hypothesized that it was more likely to have more expertise in mobile app development, which would again result in better target selection and more effective post-acquisition integration. Furthermore, if an acquirer published apps after an acquisition, I interpreted that as a pivot in business strategy towards app development, which might suggest an increased willingness of the acquirer to deploy resources towards making both the existing apps of the target's team, and the apps that they would later develop, successful.

Perfect market match was a dummy variable that measured whether the target and acquirer operated in the exact same market and industry area (e.g. enterprise software, games, social commerce, etc.). This was intended to be a proxy for how closely aligned two different businesses were in terms of their target market audience. Each company self-reports a single market classification on Crunchbase, and I accessed this via our pull of Crunchbase acquisition data. There is considerable measurement uncertainty in defining the market in which a company operates, especially since each company reports its own perspective of the market it feels best describes its operations, which might not always objectively be the most accurate description of the market in which it actually operates. This explains the unexpectedly low number of acquisition pairings that reported perfect market matches – only 63 pairs, or 14.5%.

There are arguments for both viewpoints on whether a horizontal acquisition creates more value for the target than a vertical acquisition would. For the former, one could argue that the target enjoys increased returns to scale as part of a larger platform post-acquisition; for the latter, one could argue that the benefits from diversification and cross-selling across different industries outweigh the benefits from consolidating a highly fragmented industry. Ultimately, based on the existing literature on M&A in high-technology industries, I hypothesized that being acquired by an acquirer in the same market would be better for the target.

Same region was a dummy variable that measured whether the target's and acquirer's headquarters were located in the same geographical region. I found each company's region as part of the Crunchbase acquisition pull. Crunchbase generally defines a region as a broader metropolitan area (e.g. San Francisco Bay Area, Greater New York area, etc.), but it only takes into account headquarters location, and not any satellite offices that companies might have.

Once again, the literature on geographical diversification in M&A is split, with one camp of researchers observing significant negative effects due to cultural differences and a lack of geographical specialization; and another camp observing significant positive effects due to geographical diversification and the ability to access resources (including customers) in different regions. Given that app rankings are heavily weighted towards downloads, which is naturally a function of the number of users reached, it seems like the latter argument – increased access to different geographical pools of users – is likely to outweigh the potential integration challenges faced as a result of geographically diverse deals. As such, I hypothesized that being acquired by an acquirer headquartered in the same region as the target would result in a more positive outcome for the target.

4. METHODOLOGY

The aim of this paper is to analyze how endogenous characteristics of the target, the acquirer, or the target-acquirer pairing can influence post-acquisition outcomes for the target specifically. While exogenous characteristics (e.g. market timing, position in business cycles, competitive positioning in the market, etc.) obviously have a huge impact on the outcome of the acquisition, they are challenging for parties involved in the transaction to control, and are therefore beyond the scope for this paper. Also, unlike most papers in the field today, I chose to study deal success solely from the point-of-view of the target. Few companies report financial or operational metrics of their acquisition targets separately once the acquisition closes, and hence the growth trajectory of targets post-acquisition is poorly understood. Most papers focus on metrics of the acquirer (which are much easier to track and measure), and thus deal success is usually defined solely in terms of acquirer success. In this study, I attempt to complement the existing literature on this subject by looking solely at an acquisition from the target's point-of-view.

First, I separated the apps into two pools: top free apps and top paid apps, depending on whether or not users had to pay to download these apps. I conducted my regressions on each of these pools separately. The reason for this is twofold: firstly, for ease of data manipulation – Apple ranks the top free and top paid apps in its App Store separately, and it would be near impossible to compare the #1 top free app to the #1 top paid app; secondly, apps on each of these lists tend to have very different economic characteristics, which shall be discussed in greater detail once we come to the results and discussion section.

For the purposes of this study, we have used mobile app rankings as a proxy outcome variable for the target. As previously mentioned, financial and operational metrics are rarely reported separately for targets post-acquisition, and many app-developing companies also tend to be private companies, with no obligation to report any metrics whatsoever. However, as long as the mobile app remains in existence, we can track (or impute) its ranking, providing a basis for a pre- / post-acquisition performance comparison for the target. There are two ways by which an acquisition could affect the rank of the target company's apps: firstly, it could result in performance changes on the **app level**, where **existing apps** experience a change in ranking because of resource redistribution stemming from the acquisition event. Alternatively, it could result in performance changes on the **developer level**, where **new apps created post-acquisition** perform differently than apps created prior to the acquisition due to different access to resources. We study these two effects separately as discussed below.

App-level changes: existing apps

Isolating the effect of the acquisition on app ranking is challenging, especially in the fast-paced world of mobile apps where developers are constantly re-developing and improving their offerings based on reasons that might have nothing to do with the acquisition, such as user feedback or a change in revenue model. However, in our study of apps that were released prior to acquisition, we decided to study the trends in rank change within a relatively short 2-year period centered about the acquisition date (i.e. 12 months before and after the acquisition).

Admittedly, there is a tradeoff between seeing a "clean" effect and a "full" effect. The former attempts to isolate the change in app ranking due solely to the acquisition event, by measuring the change in ranking across an extremely short time period (say, 1 month immediately after acquisition) where other exogenous factors that might affect app ranking are unlikely to have changed too much. The latter attempts to give the longer-tailed effects of acquisition enough time to occur, and measures rank change across a longer period (say, 12 months after acquisition), but risks interference from the aforementioned other factors that might influence app ranking.

Rank change for each month after acquisition is defined as the maximum (i.e. highest) ranking achieved by an app during specific 30-day time intervals immediately following the date of acquisition, minus the maximum ranking achieved by that same app during the 12-month period immediately prior to the acquisition. For example, the rank change during the x^{th} month of the acquisition would be defined as follows:

$$Rank\ change_x = Highest\ rank\ achieved\ between\ days\ 30(x-1)\ to\ 30x\ after\ acquisition$$
$$-\ highest\ rank\ achieved\ days\ 0-365\ before\ acquisition$$

I also chose to determine rank change by taking the difference in maximum ranks achieved during the respective before / after acquisition monthly periods, rather than the mean rank during this period. Anecdotal evidence and my conversations with app developers suggest that developers tend to focus on maximizing absolute ranking at any given time, since most apps have an extremely short life cycle and the very top apps are given significantly more visibility than their lower-ranked counterparts. Hence, being ranked 1st for a few days and then not ranked in the top 500 at all subsequently would be more valuable to a developer than being ranked further down in the mid-200s-300s over an extended period.

Developer-level changes: new apps

Measuring changes at the developer level requires a slightly different definition of rank change. Here, we divide the apps created by each developer into two pools: first, apps that were created prior to the acquisition date; and second, apps created after the acquisition date. I defined creation date for each app as the date on which the app first appeared in the iTunes App Store. Acquisition date was defined as the date on which the acquisition was first publicly announced. For each app that was created prior to the acquisition date, we recorded the highest rank it had ever achieved between its creation and the date of acquisition. For each app created after the acquisition, we recorded the highest rank it ever achieved between its date of creation and the end of our sample.

Once again, I take the developer's performance to be measured by the global maximum of the highest ranks achieved by the apps (e.g. if developer A created two apps which peaked at rank #1 and #400, and developer B created two apps which peaked at #200 and #201, developer A would have a relative ranking of #1 whereas developer B would have a ranking of #200). Rank change, on the developer level, is thus defined by the peak rank ever achieved by any app developed post-acquisition minus the peak rank ever achieved by any app developed pre-acquisition. Again, this methodology was largely driven by industry anecdotes that the quality of a developer is measured by the frequency and probability with which it develops hit apps.

I then used a standard ordinary least squares (OLS) regression model to estimate the impact of acquisition on rank change for apps created by any developer that was later acquired. Since each developer might have created multiple apps, I clustered the rank changes for apps by their developer IDs to account for possible correlation of app performance between apps created by the same developer. Otherwise, app rankings and ranking changes are assumed to be independent between developers. I used Stata's *cluster* option to indicate my belief that app performance is correlated within developers, with the regression equation specified below:

$$Rank\ change = \beta_0 + \beta_1 mobileOnly + \beta_2 perfectMarketMatch + \beta_3 ageDifference + \beta_4 acquirerAge + \beta_5 sameRegion + \beta_6 appsBefore? + \beta_7 appsAfter?$$

5. RESULTS

Effect of Acquisition on Free Apps

App-Level Rank Changes (Existing Apps)

To reiterate, I regressed rank change at multiple post-acquisition periods of 1 month's duration against characteristics of the target, acquirer, and the deal pairing. My baseline for app ranking prior to acquisition was the highest rank achieved by a given app during the 12-month period immediately before the acquisition was publicly announced.

Table 5 presents regression results for rank change during the 1st, 6th, and 12th monthly periods following the acquisition. I have reported detailed results for the variables' coefficients in the 1st, 6th, and 12th months following acquisition as representative of the full set of regressions done.

However, only a subset of identified acquired developers developed apps that were ranked part of the top 500 free apps during the 12-month periods before and after their acquisition, resulting in a much smaller sample size than initially expected. Furthermore, the sample size shrinks as the length of time since acquisition increases, as we lack the required data to measure the 6th or 12th month impact on acquisitions that happened near the end of our ranking dataset. Due in part to the small sample size, and the considerable number of independent variables studied, not all of the observed effects were statistically significant.

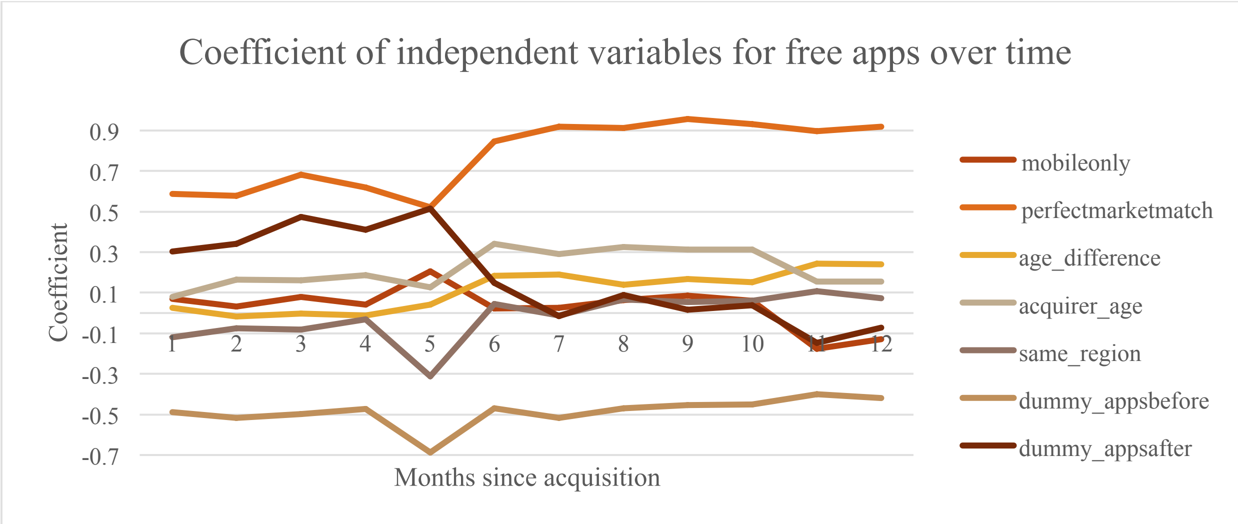
Table 5: Regression Results for Free Apps

Rank_change	1 month	6 months	12 months
Mobile only	0.0714 (0.2422)	0.0230 (0.2678)	-0.1280 (0.3109)
Perfect market match	0.5857 *** (0.1480)	0.8458 ** (0.3478)	0.9181 *** (0.3312)
Age difference	0.0249 (0.1199)	0.1842 (0.1306)	0.2402 ** (0.1394)
Acquirer age	0.0795 (0.1560)	0.3416 * (0.1784)	0.1554 (0.1731)
Same region	-0.1187 (0.1649)	0.0432 (0.1866)	0.0732 (0.2232)
Apps before?	-0.4882 ** (0.2035)	-0.4700 ** (0.1900)	-0.4188 * (0.2191)
Apps after?	0.3040 (0.2255)	0.1499 (0.2609)	-0.0709 (0.3025)
Constant	-0.7443 (0.4768)	-1.835 (0.5540)	-1.230 ** (0.4922)
Observations	188	155	123
R-squared	0.0686	0.1613	0.0805

Standard errors in parentheses
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Figure 1 below tracks the changes in coefficients for the measured variables as time since acquisition (in months) increases. This allows us to observe the timing at which the synergistic (or antagonistic) effects of certain acquisition traits kick in, and when they peak. For instance, the benefit to the target of being acquired by an acquirer in the same geographical region (see the *same_region* line) peaks within the first month of acquisition, implying a near-immediate effect.

Figure 1: Trajectory of coefficients for free apps



Overall, the trendlines suggests that the effects of acquisition can be seen fairly quickly in mobile app performance – about half of the total improvement attributable to the acquisition event is typically realized immediately, within the 1st month. There seems to be an inflection point around the 5th or 6th month, where the signs of some of the coefficients change direction (e.g. *dummy_appsafter*), or their magnitudes increase (e.g. *perfectmarketmatch*) and then stabilize again. These results seem contrary to traditional M&A literature, which suggests that the effects of acquisitions are typically only seen over a timescale of years. Perhaps, these differences are due to the underlying speed at which the mobile app market tends to evolve, with apps capturing consumers' demand only for weeks or even days at a time; or they may even suggest a structurally easier integration process experienced by mobile app developing startups, which tend to be leaner operations than other traditional companies.

Moving on now to the individual independent variables, we see that horizontal acquisitions (mergers or acquisitions between companies in the same industry, measured by the *perfectmarketmatch* dummy variable) had, as expected, a positive and significant effect on post-acquisition target performance. The effect was large (+58.6% in month 1; +84.6% in month 6; and +91.8% in month 12) and significant ($p < 0.05$ for all months; $p < 0.001$ for month 1 and month 12). Integration effects were also immediate – the target's apps saw an increase in ranking right away during month 1 post-acquisition, which persisted at relatively stable levels until months 5-6, where the target's rankings seemed to receive yet another boost, potentially from some synergies that took longer to kick in. Complete integration was also achieved relatively quickly – after peaking in month 9, the synergistic effects of being acquired by a company in the same industry stayed approximately constant until the end of the measurement period.

As expected, the coefficients on age difference and acquirer age were positive, though they were not dramatically large or significant in all cases. Each additional year of age difference resulted in a 24.0% increase in ranking at the 12-month mark ($p < 0.05$), and each additional year in the acquirer's age resulted in a 34.2% increase in ranking at the 6-month mark ($p < 0.10$). Again, the synergies were realized fairly quickly after acquisition, increasing slowly up until the 6-month mark and then staying fairly stable thereafter.

Surprisingly, being acquired by a company that had previously developed mobile apps led to a decrease in app ranking for free apps that had existed at the point of acquisition. At the 1st month mark, being acquired by a mobile app developer resulted in an immediate -48.8% decrease in ranking ($p < 0.05$), which stayed stable throughout the period of study, only decreasing a bit to a -41.9% decrease in ranking ($p < 0.10$) in the 12th month. On the contrary, getting acquired by a company that later continued to publish new apps after the acquisition was a short-term boost for the target's existing apps. This provided a boost to existing app ranking until month 5 or 6, after which the effect started to peter away to zero. The effect on rank change of being acquired by a company that continued to publish new apps was also not statistically significant for our study sample.

All other effects could not be precisely estimated, or are close to zero for the chosen time horizon and sample size.

Developer-Level Rank Changes (New Apps)

Recall that another important measure of acquisition success was defined as the target's continued ability to create and promote new, chart-topping apps. Therefore, I also carried out a regression on the change in rank between apps published by the target prior to its acquisition, and apps published post-acquisition. The results of this regression are reported in Table 6 below. In this regression, my sample was limited to apps that were published under the target's old developer ID, which unfortunately leaves out apps published by the target's team using the acquirer's developer ID. However, despite the extremely small sample size, a few of the results were nevertheless significant due to the large magnitude of the observed effects.

Table 6: Rank change for newly-created free apps

Rank_change	**Pre-acquisition vs post-acquisition**
Mobile only	-1.005 (1.003)
Perfect market match	0 (omitted)
Age difference	-1.059 (0.8465)
Acquirer age	1.495 ** (0.5297)
Same region	1.583 (1.742)
Apps before?	-4.737 *** (0.9336)
Apps after?	-1.093 (0.9754)
Constant	0.8307 (1.677)
Observations	10
R-squared	0.9569

Standard errors in parentheses
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Most of the coefficients of this regression have the same sign as their counterparts when rank change in existing apps is regressed against the same explanatory variable. The two statistically significant effects are for acquirer age (positively and statistically significantly correlated with rank change; +150% increase in the best app ranking ever received post-acquisition; $p < 0.05$) and for an acquirer that had previously published apps prior to acquisition (negatively and statistically significantly correlated with rank change; -474% decrease in the best app ranking ever received post-acquisition; $p < 0.01$).

One notable difference is the effect of a larger age difference between the target and acquirer on the ranking of the target's new apps. Referring to the previous section, we see that while a larger age difference between the target and acquirer was moderately positive for the target's existing apps (+24.0% increase in app ranking at the 12-month mark, $p < 0.05$), it actually seemed to be negative for the creation of new apps. Apps created by the target after acquisition peaked at rankings that were -106% worse than apps created prior to the acquisition. Essentially, while a larger age differential in acquisition seemed to be beneficial to the target's existing apps, it also seemed to hinder the creation of new hit apps by the target after acquisition.

Effect of Acquisition on Paid Apps

App-Level Rank Changes (Existing Apps)

I now turn to the effect of acquisition on paid apps, which I decided to study separately from free apps due to their inherently different economics. Table 7 presents regression results for rank change during the 1st, 6th, and 12th monthly periods following the acquisition. As with free apps, only a subset of identified acquired developers developed apps that were ranked part of the top 500 paid apps during the 12-month periods before and after their acquisition, resulting in a very small sample. There are also fewer paid apps on average than there are free apps. Hence, due to the small sample size, most of the observed effects within the dataset are not statistically significant.

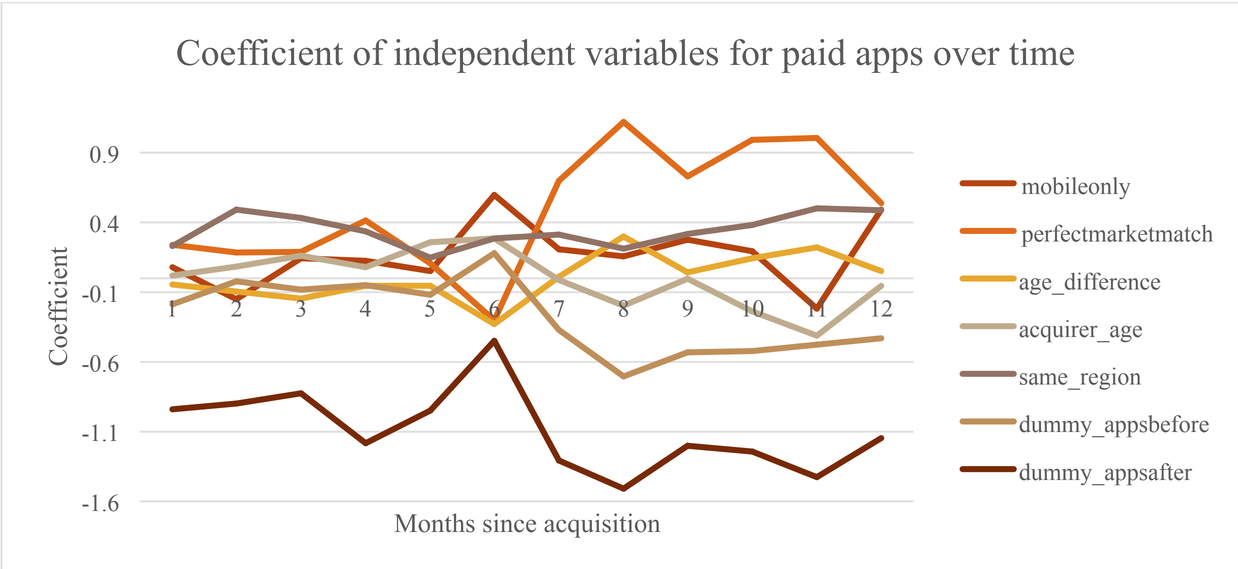
Table 7: Regression Results for Paid Apps

Rank_change	1 month	6 months	12 months
Mobile only	0.0776 (0.4693)	0.6005 (0.8186)	0.4944 (1.003)
Perfect market match	0.2419 (0.5022)	-0.3029 (0.7680)	0.5371 (0.8482)
Age difference	-0.0423 (0.1859)	-0.3283 (0.3027)	0.0527 (0.3330)
Acquirer age	0.0201 * (0.3637)	0.2877 (0.4441)	-0.0547 (0.8435)
Same region	0.2327 (0.4035)	0.2873 (0.5837)	0.4871 (0.7134)
Apps before?	-0.1870 (0.3733)	0.1807 (0.6190)	-0.4294 (0.5838)
Apps after?	-0.9379 (0.3220)	-0.4492 (0.5964)	-1.145 * (0.6693)
Constant	-0.2708 (0.9593)	-0.4492 (0.5964)	-0.1777 (2.088)
Observations	85	73	61
R-squared	0.1291	0.1140	0.1030

Standard errors in parentheses
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Figure 2 below tracks the changes in coefficients for the measured variables as time since acquisition (in months) increases. Again, since the variable *rank_change* was defined as the difference in the natural logarithms of the highest ranks reached during fixed periods before / after acquisition, the coefficient represents a percentage increase / decrease in ranking on the top paid list.

Figure 2: Trajectory of coefficients for paid apps



The data is much harder to interpret for paid apps due to the greater amount of noise involved. However, we can also see that there seems to be an inflection point around month 5 or 6, like trends we saw in the existing free app rankings. There is significantly more ranking variation for paid apps out in the later periods after acquisition, and I am unable to determine whether this variation is largely due to noise from the inherently smaller sample, or if it is a result of the different underlying economics of paid apps.

One interesting difference between free apps and paid apps is the effect associated with being acquired by a geographically proximate company (*same_region*). While the geographical proximity of the target's and acquirer's headquarters had essentially no effect on the performance of the target's existing free apps, it appears to have a positive effect of larger magnitude on the target's existing paid apps (+23.3% increase in ranking in month 1, which steadily increased to +48.7% increase in ranking by month 12). However, the observed effect was not statistically significant.

Another difference between free and paid apps is what happens when the merged entity develops and publishes apps post-acquisition (i.e. *dummy_appsafter* = 1). There was a short-lived positive effect on rankings of existing free apps. However, the effect on paid apps is consistently negative, starting at a -93.8% decrease in ranking at month 1, which fluctuates eventually increases to a -114% decrease in ranking at month 12 ($p < 0.10$).

Developer-Level Rank Changes (New Apps)

Here, we repeat the regression on rank change in paid apps at the developer-level, comparing the performance of apps created post-acquisition to that of apps created pre-acquisition.

Table 8: Rank change for newly-created paid apps

Rank_change	Pre-acquisition vs post-acquisition
Mobile only	0.7451 *** (0.000)
Perfect market match	1.725 *** (0.000)
Age difference	1.382 *** (0.000)
Acquirer age	-1.645 *** (0.000)
Same region	0 (omitted)
Apps before?	-0.3521 *** (0.000)
Apps after?	1.479 *** (0.000)
Constant	2.720 *** (0.000)
Observations	8
R-squared	1.000

Standard errors in parentheses
** p < 0.10, ** p < 0.05, *** p <0.01*

Despite the small sample size, the results were statistically significant due to the large magnitude of the effects. Again, like what we observed in the case of free apps, most of the coefficients of this regression have the same sign as their counterparts when rank change in existing paid apps is regressed against the same predictors of performance.

Two obvious differences stand out: a larger age difference between the target and the acquirer was mildly negatively correlated with rank increases for existing apps, but seems to have a strong, positive impact on the ranking of newly developed paid apps post-acquisition. Newly developed paid apps saw a statistically significant ranking increase of +138% relative to paid apps created before the acquisition ($p < 0.01$). This is perhaps explainable by viewing paid apps as substitutes for one another – where newly created paid apps substitute (and therefore cause a decrease in ranking) for paid apps created by the same developer in the past. It is also worth noting that free apps experience the exact opposite of this phenomenon: a larger age difference is better for existing free apps, but worse for the creation of new free apps.

Another area of difference lies in the effect of the merged entity developing new apps after acquisition. As discussed above, this had a negative effect on existing paid apps. However, it seems to have a positive (+148%) and statistically significant ($p < 0.01$) effect on the performance of newly-created apps. Again, this is likely attributable to the fact that paid apps are more likely to substitute for each other, resulting in contrasting and opposing effects observed for existing apps compared to newly-created ones.

6. DISCUSSION

The most striking takeaway from these results is the sheer speed at which the effects of acquisition become apparent in the target companies. Where significant and measurable, the effects are observed almost immediately after the acquisition closes – at any rate by the end of the first month after the acquisition. Furthermore, by the 6th month after the acquisition date, the effects of acquisition have essentially stabilized, and there is little further ranking change attributable to any of the deal factors studied here from that point onwards. Since no further ranking change occurs, it is reasonable for us to conclude that integration of the acquisition has been fully completed by that point.

Apart from being objectively fast, acquisition integration in mobile app developing companies is also significantly faster relative to acquisition integration in traditional industries, where merging companies can take years to fully integrate their operations. This is likely due to the nature of the mobile app industry and modern high-technology startups in general: companies in this industry tend to be small, with business models that are heavily dependent on technology, and laser-focused product strategies. The high dependence on technology makes them much more scalable than other companies which rely more on tangible assets, and traditionally, has been used to explain why these mobile app developing companies tend to enjoy accelerated organic growth. I posit that these characteristics also lend themselves well to accelerated inorganic growth through mergers and acquisitions. Startups tend to be easier to integrate post-acquisition: they have few tangible assets and much of their business value lies in the strengths and skills of the engineering team. Integration for a startup means simply onboarding and re-training a (usually small) team of software engineers, compared to integration for a traditional, non-technology focused company, which might necessitate re-engineering entire production lines or supply chains – using up significant time, energy, and resources.

As acquisition targets, mobile app developing startups also seem to benefit strongly from their acquirers' inorganic growth strategies. Most of the coefficients observed in our regressions are positive and large for ranking change of existing apps, suggesting that many of these acquisition targets enjoyed a huge boost in consumer popularity after being acquired, presumably attributable to some effects arising from the acquisition. As discussed earlier, the results are quickly apparent and integration is usually completed by the 6th month following the close of the acquisition. However, the positive effect of these integrations also become significant rapidly – the immediate effect of the acquisition, measured by the ranking change in existing apps within the first month post-acquisition, is usually huge. For many variables (e.g. *perfectmarketmatch* for both existing free apps and paid apps; *same_region* for paid apps), the effect observed in the first month alone represents more than half of the total observable change over the entire 12-month period tracked post-acquisition. Referring to Figures 1 and 2 in the discussion section – the graphs of the coefficients of independent variables on the rank change of existing apps over time – we see that even in the first 6 months post-acquisition, the magnitude of additional changes in the coefficients between months 2-6 are small relative to the huge surge in month 1 alone. These large positive effects also persist over time: the coefficients on *perfect_market_match*, *same_region*, and *age_difference*, just to name a few, remain positive and large even at the 12-month mark post-acquisition for both existing free and existing paid apps.

Why do mobile app developing startups experience such positive returns to acquisitions in general? One possible explanation lies in the increased access to resources that most of these acquisition targets enjoy post-acquisition. Many of these startups tend to be small and highly resource-constrained, whereas their acquirers tend to be larger and more mature companies with greater access to resources. Therefore, due to the larger differential in resource accessibility between their pre-acquisition and post-acquisition states, mobile app developing startups tend to experience an outsized positive effect after being acquired.

The theory of differential access of resources also potentially explains why acquisition has a much larger positive effect on the ranking of free apps compared to paid apps: free apps can be developed with a very limited resource pool, whereas successful paid apps require both a larger quantity of and more sophisticated resources to create. However, once the app has been created, a paid app usually requires fewer resources from its developer to achieve commercial success: it might already be generating some revenue, which essentially allows the app to subsidize, or even pay for, its own commercialization. On the other hand, a free app may require a substantial investment of new resources for marketing or promotional campaigns before it achieves commercial success.

In the case of mobile app developing startups, a top-ranked paid app would be analogous to a successful, revenue-generating product. Therefore, we can understand acquisitions of startups that primarily develop paid apps as more similar to acquisitions in traditional industries, where there is a combination of two or more product lines in the resulting entity. Having already had access to the resources necessary to overcome the barriers to entry to developing a successful product line, developers who primarily create paid apps benefit less from acquisition than developers who primarily create free apps (and by inference, might not necessarily have access to the same level of resources) because the increase in resource access as a proportion of existing resources is much smaller for them.

Although the speed of integration and the positive effects of acquisition were all somewhat expected observations given the rapidly developing and lean nature of startups, some observed results were surprising to us. For instance, being acquired by an acquirer that had previously developed apps prior to acquisition was, overall, negative for both existing free and paid apps. Initially, I had expected prior app-developing experience to be positive for the target, because it suggests that the acquirer might have additional product-related expertise, theoretically aiding in target selection, deal integration, and post-merger strategy.

However, my expectations would only have held true if all acquisitions were made solely for the purposes of acquiring the target's product (in this case, apps). Instead, we know that acquisitions can happen for a variety of non-product-related reasons. As previously mentioned, acquihires – acquisitions made primarily for the sake of recruiting a company's key employees – are becoming an increasingly common phenomenon in the startup world. In an acquihire, the software engineers at the target company might be redeployed to work on other products after the acquisition closes, relegating the maintenance of existing apps to secondary importance. Acquisitions might also be made for the purposes of eliminating or reducing competition – a company might acquire its rivals' apps for the sole purpose of shutting them down, or incorporating some of their apps' key features into an acquirer-branded version of the same product. Targets acquired for any of these reasons (amongst others) would be likely to experience very different post-acquisition effects than targets acquired for purely product-related reasons.

Our theory is further supported by the differences in effect on existing apps and new apps. Some deal variables resulted in positive effects for existing apps, but were negative for the creation of new apps (e.g. *age_difference* for free apps; *dummy_appsafter* for paid apps). Again, the existence of non-product-related reasons as motivations for acquisition could help us understand these seemingly counterintuitive results: a target might have been acquired for its engineers, who were then re-deployed to work on projects deemed of greater strategic importance to the acquirer. As such, the target's engineers are unlikely to devote as much energy as before to developing top performing hit apps, resulting in a blow to the quality of new apps created. In sum, the prevalence of non-product-related reasons for acquisition could help us explain the unexpected results observed; and in turn, the observed results provide further evidence that acquisitions do commonly occur for non-product reasons as well in the mobile app industry.

7. CONCLUSION

In this paper, I developed a novel approach to study the post-acquisition performance of mobile app developing startups, which allows us to identify and understand acquisition-related effects from the target's point-of-view. The post-acquisition performance of acquisition targets has historically been challenging to observe due to a lack of target-specific data published by the merged entity, but we have managed to approximate target performance via a comprehensive dataset of daily rankings for apps created by a developer that was later acquired. By tracking the change in ranking over a one-year period after an acquisition, we can observe several interesting trends pertaining to the speed and magnitude of acquisition effects in mobile app developing startups, and how they might differ from acquisition effects in traditional industries.

Acquisitions create a huge amount of value amongst mobile app developing startups. I find that acquired startups generally experience significant, positive benefits from acquisition, which rapidly become apparent in target performance post-acquisition, typically on the timescale of months, or even days. Essentially, not only are startups capable of rapid organic growth – a known fact in the entrepreneurial community – they are also capable of (and can benefit significantly from) rapid inorganic growth. Success stories, where the target's apps experience large, rapid growth post-acquisition, allow us to make inferences about when and how the acquirer's resources might be particularly valuable to the target – for example, providing entry into a new market of consumers, or allowing the target to realize significant economies of scale via horizontal integration.

However, situations where the theorized benefits from acquisition are not realized as expected also tell us a lot about motivations for acquisitions in the startup industry. Our data allow us to observe situations where the target's products essentially disappear or experience abnormally rapid declines in ranking post-acquisition. These situations suggest that the acquisition was clearly not carried out for the purposes of integrating the target's products into the acquirer's portfolio, and thus empirically provide evidence for the prevalence of non-product-related motivations for startup acquisition. Examples of such non-product-related motivations include acquihires or acquisitions to eliminate competition for scarce resources (e.g. users' attention and home screen space), but the sheer variety of unexpected motivations fueling startup acquisitions today could be the subject of a paper all on its own.

Ultimately, the startup boom in Silicon Valley has persisted for some years, and many of the companies spawned during this boom are starting to mature and move into the next stages of their corporate life cycle. Be it an early exit, or further growth, this next stage is likely to involve M&A in some form or another. This study has been a valuable opportunity to study one of the newest and most exciting industries in existence today, and shed some light on the economics of and motivations for M&A activity within it. To the best of our knowledge, this is also the first time conventional accepted wisdom about M&A in startups has been measured and codified into academic strategy scholarship. As more startups start to consider M&A as a growth strategy or exit option, I expect this field to provide ample opportunities for new research and knowledge creation.

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