Gatekeepers and Kingmakers: Do Superplatforms Distort Digital Competition? *

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Abstract

The rising dominance of superplatforms raises concerns about conflicts of interest and potential externalities on innovation and entrepreneurship, as they simultaneously act as marketplace gatekeepers and strategic investors. Analyzing Google's dual role in Google Ventures (GV) and the Android marketplace, we find that GV-backed startups receive 115% more app reviews, 12% higher ratings, and 77% fewer bug-related complaints relative to their iOS counterparts following GV investment—even without major quality enhancements via app updates. These improvements stem from selective negative-review removal and targeted platform promotion. Our findings highlight platforms' exploitation of conflicted roles to extend competitive advantage, challenging platform neutrality.

Keywords: Market Concentration, Superplatforms, Platform Neutrality, Innovation externalities, Conflicts of interest

JEL Codes: D42, D83, G24, O32

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1 Introduction

The global economy continues its unprecedented shift toward digital commerce and knowledge-intensive activities. UNCTAD's 2024 Digital Economy Report reveals the scale of this transformation: e-commerce sales across 43 major economies surged to $27 trillion in 2022, up from $17 trillion in 2016. This massive digital marketplace operates within economies that collectively represent three-quarters of the world's $100 trillion GDP, highlighting the digital sector's central role in modern economic activity.[1] Yet this digital transformation has fostered dangerous levels of market concentration. Just seven digital "super platforms"—Microsoft, Apple, Amazon, Google, Facebook, Tencent, and Alibaba—now control two-thirds of the digital economy's total market value. This alarming pattern extends to the U.S., where the "Magnificent Seven" tech firms have seized 29% of the S&P 500's market capitalization and driven two-thirds of its appreciation in 2023.[2]

This consolidation of market power manifests itself in multiple troubling dimensions. Alphabet (Google), Apple, Amazon, Meta (Facebook), and Microsoft not only dominate the digital marketplaces that now govern countless economic transactions but also aggressively pursue strategic acquisitions and venture capital investments, weaponizing their exceptional market valuations. Perhaps most concerning, these firms control critical technological infrastructures that other companies must depend on for survival, innovation, and product development.

The convergence of these roles—platform owner, investor, and technological gatekeeper—threatens market integrity through inherent conflicts of interest and self-preferencing behavior. This multifaceted dominance enables big tech firms to manipulate competitive dynamics within their platforms and potentially distort broader market outcomes to benefit their affiliated enterprises. While regulatory scrutiny of self-preferencing has increased, existing research has narrowly focused on direct product competition within platforms, dangerously overlooking how indirect minority investments by platform owners might further extend their already outsized competitive advantage.

In this paper, we examine these critical issues using the mobile app market as our empirical laboratory, specifically investigating Google's dual role as a platform operator and venture investor through its subsidiary, Google Ventures (GV). As an example, after Google Ventures led a $361.2 million

[1] https://unctad.org/system/files/official-document/der2024_en.pdf

[2] https://www.reuters.com/markets/us/can-sizzling-magnificent-seven-trade-keep-powering-us-stocks-2024-2023-12-28/

investment in Uber in 2013, Google Maps began integrating a direct option to request Uber rides, illustrating how platform-backed investments can yield tangible competitive advantages. By analyzing data from Google Play and Apple's App Store, we uncover and quantify two insidious mechanisms through which Google appears to tilt the competitive landscape: first, by boosting the visibility of GV-backed apps through preferential recommendations that dramatically increase user discovery; and second, by selectively scrubbing negative reviews that mention bugs and flaws, artificially inflating ratings. These practices do not merely represent theoretical concern—they fundamentally distort market dynamics, potentially strangling innovation, and raise urgent policy questions about whether digital gatekeepers can ever truly act as neutral referees while simultaneously betting on specific players.

Our findings reveal a striking pattern of preferential promotion: apps backed by Google Ventures enjoy dramatically enhanced visibility across the Google Play store. When users browse an app, they're shown recommendations for "similar apps" they might also enjoy—a crucial discovery channel that can make or break an app's success. Our analysis reveals that, within a network of 9,225 apps, GV-backed apps appear in these coveted recommendation slots an average of 30.42 times—more than four times as frequently as the mere 6.85 appearances for apps backed by venture capital firms without prior syndication history with GV. This visibility advantage isn't explained by app quality or popularity—it persists even after we rigorously control for app age, download counts, user ratings, and app genre classifications. This digital equivalent of prime retail shelf space represents a powerful, yet largely invisible, competitive edge for Google's investment portfolio.

We also find evidence of negative review curation, i.e., negative and bug-related reviews are disproportionately removed for GV-backed apps on Google Play, leading to an artificially inflated average rating. Comparing two vintages of review data collected in July 2023 and January 2024, covering the same period, July 2022 to June 2023, we find that 1 and 2-star reviews (i.e., negative reviews) and bug-related reviews for GV-backed apps are 3-4 times as likely to be removed compared to those from apps associated with other VCs that have never co-invested with GV. In contrast, we observe no such difference in negative review deletions between GV-backed apps and other apps on Apple's App Store. We analyze whether the observed curating pattern is due to the potentially disproportionate amount of inappropriate reviews that might violate Google Play's policy and thus induce more platform removals. Using a deep learning model-based analysis, we find little semantic difference between the removed negative reviews and the retained negative reviews.

These preferential treatments may lead to greater success for the startups' Android apps, especially compared to their iOS apps, where such preferential treatment is absent. For example, promotion of the platform through frequent suggestions of "similar apps" may enhance the download and usage of the app. The selective removal of negative and bug-related reviews could lead to artificially inflated ratings, misrepresenting the apps as higher quality than they truly are.

To investigate the causal impact of Google Play's preferential treatments on the performance of GV-backed Android apps, we conduct a difference-in-differences (DiD) analysis using these apps' iOS counterparts as control groups. Our identification assumption is that, while the Android and iOS versions of the same app are developed by the same startup, offering identical functionalities and catering to similar-sized customer bases, Google Play's preferential treatments affect only the Android apps. As a result, our empirical strategy helps disentangle treatment effects from selection effects, a challenge inherent in the VC literature (see Da Rin et al., 2013, for a survey). We focus on three key performance metrics derived from app reviews: review volume, average rating, and incidence of bug-related complaints. These metrics offer insights into the popularity of the app, user satisfaction, and perceived quality of the app.

We find significant improvements in the performance of portfolio firms' Android apps relative to their iOS counterparts following GV investments: a 115% increase in review volume, a 12% increase in average rating, and a 77% reduction in bug-related reviews. Benchmarking GV's treatment effects against those estimated from 127 other venture capital companies that have invested in at least five startups in the sample, we find that GV ranks in the 91st percentile for volume treatment effects, the 90th percentile for rating treatment effects, and the 98th percentile for bug reduction treatment effects. GV's overall treatment effect ranks at the top among all 128 VCs. This evidence underscores GV's exceptional capacity to boost the Android app performance of its portfolio firms. Importantly, these changes occur independently of app updates, which are the primary method developers use to improve app quality. Thus, the improvements in user engagement and satisfaction observed in Android apps may not stem from intrinsic enhancements facilitated by GV's technical guidance but are instead likely a result of preferential support provided by the Google Play platform.

Our study mainly contributes to the literature on market concentration. Recent research highlights the persistent increase in corporate concentration in the U.S. economy over recent decades, with technological innovation often identified as a key factor in increasing barriers to entry (Grullon et al., 2019; Kwon et al., 2024). Yet, the welfare implications of rising concentration remain ambiguous, especially in today's knowledge-driven economy. On the one hand, market concentration could promote innovation through improved coordination and economies of scale (Baumol, 2001). On the other hand, concentration could dampen competition, hinder entrepreneurial activity, and exacerbate inequality. For example, Autor et al. (2020) show that the labor share of value-added declines as industries are increasingly dominated by "superstar" firms. Gofman and Jin (2024) find that the dominance by big tech firms in areas such as artificial intelligence triggers a significant academic brain drain, which impedes entrepreneurial formation and innovation. Our paper contributes to this debate by empirically investigating how big tech firms' multifaceted roles—as both platform operators and strategic investors—impact market fairness and competition in the rapidly expanding digital economy.

Our study also contributes to the literature on platform economics. Platform ecosystems create substantial value for their owners by fostering innovations from external partners (Benzell et al., 2023; Parker et al., 2017). Although platform-based markets are fundamentally dependent on attracting and retaining diverse participants (Parker and Van Alstyne, 2005; Rochet and Tirole, 2003), policymakers and the media have increasingly raised concerns about platform encroachment, where platform owners compete directly with third-party sellers on their platforms. Recent theoretical work has examined the implications of this self-preferencing (Anderson and Bedre-Defolie, 2021; De Corniere and Taylor, 2019; Etro, 2023; Hagiu et al., 2022), and empirical studies have documented how platform owners such as Amazon strategically enter the markets of third-party sellers (Crawford et al., 2022; Zhu and Liu, 2018). In addition, a comprehensive review by Cheng et al. (2024) documents the evolution of empirical platform research and highlights growing concerns about platform governance and competitive dynamics. Their analysis shows a significant shift in research focus towards studying platform orchestrators' strategic decisions and their impact on platform participants, particularly regarding issues of market power and preferential treatment.

Although prior research has examined how the entry of platform owners affects complementary innovation in mobile app markets (e.g., Foerderer et al., 2018), with mixed evidence suggesting both positive innovation effects through increased consumer attention and negative effects through competitive displacement, our study extends this line of work by examining how platform-affiliated venture capitalists can systematically shape innovation outcomes through preferential platform treatment of their portfolio companies. This is particularly important as platforms expand their influence through strategic investments. For example, Wen and Zhu (2019) show that when Google enters the market, developers turn away from competing directly and instead focus on creating innovative new apps. This natural reallocation of development resources away from redundant efforts ends up benefiting consumers, although the long-term implications for market competition remain unclear. We contribute to this literature by highlighting a form of self-preferencing in which platforms extend preferential treatment not to their own products but to entities in which they have invested. This expansion of the self-preferencing concept introduces a new dimension to the discussions on platform neutrality and competitive fairness in digital marketplaces, particularly as platforms increasingly blur the lines between their roles as market operators and strategic investors.

Venture capital has long been recognized as a catalyst for innovation and growth within the startup ecosystem. Previous research suggests that venture capitalists provide not just funding, but also guidance and expertise that can be crucial to the success of a new venture (Chemmanur et al., 2011). For example, the surveys by Kaplan and Strömberg (2003) and Gompers et al. (2020) have detailed the ways in which VCs engage with their portfolio companies. Previous research finds that this type of involvement improves the outcomes of startup businesses, such as the introduction of new products (Hellmann and Puri, 2000), the professionalization of firm business practices (Hellmann and Puri, 2002), and the recruitment of talent (Amornsiripanitch et al., 2019; Bottazzi et al., 2008). These improvements ultimately lead to better startup performance and successful exits (Bernstein et al., 2016; Ewens and Sosyura, 2023). In addition, previous research has shown that corporate venture capital (CVC) can be driven by various strategic objectives. Across these lines, in their study of Chinese CVCs, Dushnitsky and Yu (2022) find that rather than pursuing technological capabilities, companies in emerging markets are more attracted to startups that can help them harness rapid market growth and expansion opportunities. We contribute to this literature by identifying a new value-adding channel for venture capital companies when they are also platform owners.

2 Data and sample construction

2.1 Startup sample

We obtain data on VC investment deals from the London Stock Exchange Group (LSEG) Workspace. This data set provides comprehensive transaction details for VC investments, including the date of the funding round, the investment amount, the investment stage, and the participating investors. Given the study's focus on the effect of VC investments on startups with mobile apps, the analysis is confined to VC deals transacted from 2008 to 2022, a period in which the app economy started to emerge and grow. We also obtain startup exit data up to 2023 from the LSEG Workspace.

Prior research finds that VCs may benefit from an enhanced flow of information through syndication networks (Sorenson and Stuart, 2001). To examine the possibility that the advantages afforded by the platform could extend to VCs that have a syndication history with GV, we categorize the sample VCs into three groups: GV; connected VCs, which have established some degree of connection with GV through co-investment during the sample period; and other VCs, which have never co-invested with GV in any startups.

Our analysis examines U.S.-based startups and their mobile apps available in the U.S. market. To identify apps associated with the sample startups, we search for the startups' names and web URLs on Google Play, which suggests the most likely apps connected to the target startups. We then collect the developers' names and web URLs from the suggested apps and perform fuzzy matching on the names and URLs between the startups and the developers. To maintain a clean analysis, each developer is matched to only one startup.[3]

To investigate GV's influence on startups' performance through the Google Play platform, we compare the performance of startups' Android apps to their iOS counterparts. This approach requires us to limit the sample to startups with both Android and iOS versions of their apps. For all startup-developer pairs, we first gather data on their Android apps. Then, we manually search for the corresponding iOS apps in the App Store. We define an "app pair" as the Android and iOS versions of the same app. Figure 1 presents Uber as an example of an app pair on the two platforms. The final sample consists of 1,436 app pairs developed by 1,024 startups, including 57 apps backed by GV, 287 apps backed by VCs with no syndication history with GV, and 1,092 apps backed by VCs that have syndicated with GV. Within this sample, GV is one of the most active investors in app-developing

[3]In rare cases where a developer is fuzzy-matched to multiple startups, we use the following procedure. First, we prioritize matching a developer to a startup that has been invested by GV. Next, we consider matching a developer to a startup financed by connected VCs. If none of the matched startups is associated with GV or connected VCs, the developer is then assigned to a startup backed by other VCs. In situations where multiple matched startups fall within the same VC category, the developer is assigned to the startup that has secured the highest total funding amount during the sample period.

startups. With investments in 42 of the sample startups, GV ranks 7th among the 1,816 VCs in terms of the number of invested startups in our sample.

2.2 App metadata

The app metadata, which provides cross-sectional information about the apps, was collected in July 2023. Each platform provides distinct sets of variables in the metadata. Specifically, the metadata for Android apps from their main pages on Google Play include details on developer name, app release date, total number of downloads, app genre, and the mean rating[4]. Panel A of Table 1 presents the summary statistics for the metadata of sample Android apps. The metadata for the iOS apps are from the apps' main pages on Apple's App Store. These metadata include information on developer name and app release date[5].

2.3 App reviews and performance metrics

We use app reviews to construct performance metrics for startups. Each review on both platforms includes two elements: a star rating from one to five stars (with five being the highest) and a text review. Moreover, each review provides the exact timestamp of the posting, which is accurate to the second, and a unique identifier. App reviews often contain specific information about apps, such as reports of app bugs, suggestions for new features, sharing of user experience, and non-informative comments that simply repeat the given star rating in text form (Maalej et al., 2016).

We collected the Android (iOS) app reviews for the first time in July 2023 (September 2023), covering the time period from each app's release date to June 2023. We scraped Android app review data using a public API and obtained iOS app review data from a third-party API.[6] Since the release dates for the Android and iOS versions within each app pair may differ, we restrict the analysis to the period following the launch of both versions to allow for cross-version comparison. The final sample consists of over 28 million reviews for Android apps and over 6 million reviews for iOS apps over the period from January 2009 to June 2023.

We construct three metrics to evaluate app performance:

[4]The mean rating is derived from all user ratings, with or without text reviews.

[5]We supplement any missing release date with the information from https://www.data.ai

[6]See https://pypi.org/project/google-play-scraper/ for the API through which we obtain the Android app review data, and https://serpapi.com for the API through which we obtain the iOS app review data.

- *Log(review volume)*: the natural logarithm of one plus the number of reviews for each app version within a specified time period. This metric serves as an indicator of the app's popularity. The review volume is a proxy for user base: for the sample Android apps, the correlation between the total number of reviews and the total number of downloads is 0.65 (T= 32.07), with a mean review-to-download ratio of 0.03%. Moreover, since app reviews can only be submitted by users who have downloaded the app on both platforms, review volume also reflects user engagement levels.

- *Mean rating*: the average star rating derived from app reviews over a specific time period. This metric measures the level of satisfaction of the app users.

- *%Bug*: the proportion of bug-related reviews that mention keywords associated with app bugs for a given time period. The set of keywords indicative of bugs includes: "bug", "lag", "crash", "freeze", "glitch", "error", "buggy", "inconsistent", "unstable", "crashing", "lagging", "malfunction", "defect", "flaw", "disruption", and "shutdown". We first lemmatize each review and then check for the presence of any bug keywords from this list. We label a review as bug-related if it contains any of these keywords. These reviews, also referred to as bug reports, serve as crucial indicators of the app's perceived quality, with a higher percentage of bug-related reviews indicating lower perceived quality.

Panel B of Table 1 presents the summary statistics for the three metrics calculated on a quarterly basis for all the sample apps. On average, the sample Android apps receive 730 reviews per quarter, with a mean rating of 3.40 and 6.0% of reviews mentioning app bugs. In comparison, the iOS counterparts receive an average of 157 reviews per quarter, with a mean rating of 3.23, and 8.1% of reviews containing bug-related information.

Panel C of Table 1 presents the summary statistics specifically for apps developed by GV-invested startups (GV apps). This sample includes app pairs that have both the Android and iOS versions available at least two quarters before the quarter of GV's first investment in the startup. The Android (iOS) version of the GV apps receives an average of 2,528 (661) reviews, with a mean rating of 3.66 (3.69), and 4.4% (4.6%) of reviews mentioning bug keywords. Both the Android and iOS versions of the GV apps demonstrate greater popularity, higher user satisfaction, and higher quality than the average app in the sample.

2.4 Second-time data collection of app reviews

To explore whether GV actively engages in review curation for its portfolio firms with Google's control over the Google Play platform, we collected a second snapshot of reviews for the sample Android apps in January 2024 and for the sample iOS apps in September 2024. For both platforms, we identify potential review management based on changes in review volume across snapshots during the same time period (from July 2022 to June 2023). To address concerns about incomplete data collection, we include only reviews from the second snapshot that match those in the first snapshot based on their unique review identifiers. Furthermore, we limit our analysis to apps with non-zero reviews in both snapshots from each platform. The final sample consists of 1,255 Android apps and 1,083 iOS apps, including apps backed by GV, apps backed by other VCs that have never co-invested with GV in any startups, and apps backed by connected VCs that have established syndication relationships with GV.

The initial data snapshot from Google Play, captured in July 2023, comprises a total of 5,392,404 reviews spanning the 12-month period from July 2022 to June 2023. In contrast, the second data snapshot from Google Play, taken in January 2024, includes 5,188,977 reviews for the same sample apps, indicating that 3.77% of the reviews were removed in the 6-month interval between the two data collection points. For the iOS apps, the initial data snapshot that we collected in September 2023 from Apple's App Store contains 956,519 reviews for the same 12-month period. The second snapshot, which we collected in September 2024, includes 908,823 reviews, showing a 4.99% removal rate over the 12-month period.

Figure 2 presents a detailed breakdown of the monthly review volume for both snapshots from the two stores, revealing a systematic pattern of review removal across both platforms over time. Interestingly, this trend of review deletion is more pronounced for more recent time periods across both platforms, suggesting an active management of reviews by the platforms that disproportionately affects newer reviews. This finding raises questions about the potential reasons behind the platform's review management practices and their impact on the overall user experience and perception of the apps.

According to Google Play's official policies, user reviews can only be deleted under two circumstances: either by the individuals who originally posted them or by the platform itself if the review content is found to violate Google Play's guidelines. This policy aims to maintain the integrity and reliability of the review system while providing a mechanism for addressing inappropriate or misleading content.[7][8] Apple enforces similar policies for regulating user reviews on its App Store.

2.5 App update frequency

The changes in the app performance metrics could be potentially attributable to the intrinsic improvements of apps through updates. To explore this potential explanation, we collected the update history for both Android and iOS versions of GV apps from https://www.data.ai, a platform offering comprehensive data on the mobile app market.[9] Panel C of Table 1 reports the summary statistics of quarterly update frequency for GV apps. Android versions are updated an average of 6.28 times per quarter, compared to 6.11 times for their iOS counterparts. Thus, GV-backed startups appear to have updated their apps on the two platforms at a similar frequency.

2.6 App visibility

GV may enhance the visibility of apps developed by its investees by strategically promoting their Android apps on Google Play. In light of a feature of Google Play that each app may suggest a list of other apps as its "similar app" on its home page, we construct a measure of app visibility based on the frequency an app appears as a "similar app". The more often an app is recommended as a similar app, the higher its visibility on the platform. Since collecting data on all apps and their recommendations is impractical, we set the scope of data collection with the premise that apps are most likely to appear as similar apps for the apps they themselves suggest. Therefore, we collect data on similar apps from the home pages of the sample Android apps on Google Play. Our sample of 1,436 Android apps is associated with 9,225 unique similar apps. We then gathered the similar apps recommended by each app in this network. Thus, we measure app visibility by the frequency of each app's appearance as a similar app within this network of 9,225 apps. On average, GV apps are recommended 30.42 times as similar apps within this app network, compared to 6.85 times for apps backed by other VCs.

We further categorize the app visibility metric into two types: within-category visibility and cross-category visibility. The former quantifies how frequently each app appears as a "similar app" to other

[7] See https://support.google.com/googleplay/answer/4346705

[8] See https://play.google/intl/en_bs/comment-posting-policy/

[9] We exclude updates that miss the dates from the sample. This issue is mainly observed among some of the earliest app updates prior to 2011.

apps within the same genre, while the latter measures how often each app appears as a "similar app" to apps from different genres. Apps promoted by other apps from different genres likely reflect more of the platform's promotional preferences, as these apps have less in common. We also track the number of unique genres among the apps that recommend the focal app as "similar" to measure the degree of cross-category promotions. Our interpretation of this measure is that an app is more likely to have been strategically promoted by the platform if it shows up as a "similar app" on a greater variety of apps' pages.

3 Strategic content moderation: Evidence of differential review filtering for GV-Backed applications

In this section, we explore two potential channels through which GV may provide preferential treatment to its investees on its Google Play platform. Our analysis focuses on comparisons between Android apps developed by startups backed by GV with those developed by startups backed by other VCs, i.e., VCs that have no prior co-investment relationship with GV.[10]

3.1 Similar app suggestions

The first channel is through "similar apps" suggestions. The Google Play platform offers various promotional channels for Android apps. One such service is the "app campaign", a paid promotion that advertises apps across Google's extensive properties, including Google Search, Google Play, YouTube, and Gmail.[11]. This service highlights Google's significant influence on app visibility. As a result, startups backed by GV may have access to or benefit from these promotional services, potentially leading to a disproportionate increase in the popularity of their Android apps compared to those of their competitors.

As described in Section 2.6, we create a measure of app visibility based on the frequency of each app's appearance as a "similar app" within the network of 9,225 apps. Google Play's recommendation algorithm for similar apps likely considers factors beyond apparent similarity between apps. For example, the Uber app, developed by a GV's portfolio company, is suggested as a similar app for seemingly

[10] We exclude VCs that have prior co-investment experience with GV, which we refer to as "connected VCs", from the main analysis, considering the possibility that startups may also benefit from this type of VCs' connection with GV by receive preferential treatment on Google Play. We provide evidence consistent with this conjecture in Section 6.

[11] See https://support.google.com/google-ads/answer/12575501

unrelated apps like Adidas and LinkedIn. Conversely, these two apps do not list the Lyft app, Uber's direct competitor, as a similar app. Additionally, the Uber app appears 100 times as a similar app within the app network, whereas the Lyft app appears only 76 times, despite both providing similar services. Such discrepancies suggest that the recommendation algorithm could be influenced by the strategic interests of the Google Play platform.

Table 2 highlights significant disparities in the visibility of apps. GV apps are recommended as similar apps an average of 30.42 times. Of these recommendations, 10.46 times are from apps within the same genre, while 19.96 times come from apps across different genres. Moreover, GV apps, on average, are recommended by apps from 4.89 different genres. In contrast, apps backed by other VCs are recommended as similar apps only an average of 6.85 times, with 3 recommendations from the same genre and 3.85 from different genres. Additionally, these apps are recommended by apps from 1.18 genres on average. GV apps' advantage in platform visibility over apps backed by the other VCs is statistically significant along all these dimensions.

To further validate the relationship between app visibility and VC types, we estimate the following cross-sectional Poisson regression:

$$\text{Visibility}_i = \beta_0 + \beta_1 \text{GV}_i + \beta_2 X_i + \epsilon_i \tag{1}$$

In Equation (1), the dependent variable Visibility_i is the visibility of Android app i measured in the four different ways mentioned above: total number of appearances as "similar app" (*Overall visibility*), number of appearances as "similar app" on apps of the same genre (*Within-categoary visibility*), number of appearances as "similar app" on apps of different genres (*Cross-categary visibility*), and the number of different genres where the app shows up as a "similar app" (*# Visible categories*). *GV* is a binary variable that equals one for GV apps. X_i refers to control variables, including app age, the natural logarithm of the total number of downloads, mean rating, and app category (i.e., genre) fixed effects.

The Poisson regression estimates presented in Table 3 reveal a strong positive relationship between GV ownership and app visibility, even after controlling for app characteristics and category fixed effects. The coefficient estimate for the indicator variable *GV* is positive and statistically significant across all visibility measures. Column 1 indicates that GV apps have an overall visibility 178% (i.e.,

$e^{1.022} - 1$) higher than apps backed by other VCs. This disparity is primarily attributable to cross-category visibility, as suggested in column 3: GV apps exhibit 292% (i.e., $e^{1.366} - 1$) higher cross-category visibility compared to their same-genre rival apps backed by other VCs. Moreover, column 4 highlights that GV apps are featured as similar apps in 143% (i.e., $e^{0.886} - 1$) more genres than their same-genre rival apps backed by other VCs.

We also consider the position at which GV apps are presented on the list of "similar apps". Table 4 presents the visibility rank of GV apps and other-VC apps measured based on the position of each app on the list of "similar apps" suggestions. We report the visibility rank for all the "similar app" suggestions (*Overall rank*), suggestions by apps from the same genre (*Within-category rank*), and suggestions by apps from different genres (*Cross-category rank*). We also present both the absolute rank and the (reversed) percentile rank, with a lower value suggesting a higher rank for both measures. The results suggest that, while GV apps, on average, rank marginally higher than other VC apps when listed as "similar apps", the differences are not statistically significant.

The analysis of "similar apps" suggestions reveals that Google might have supported their investees by enhancing their apps' visibility on the Google Play platform, particularly by promoting them to users as "similar apps" when they are not. These results suggest a significant promotional advantage enjoyed by GV-backed apps within the Google Play ecosystem, potentially enabling greater user reach and engagement.

3.2 Review curation

Review curation is an important aspect of platform management, as it can shape the perceived quality and user sentiment surrounding an app. Differential treatment in review curation across GV and non-GV backed apps could provide insights into the potential influence of GV on the Google Play platform. To investigate this, we turn our attention to the review data. App reviews posted on Google Play can be removed either by the app user who wrote them or by the platform itself if the review content is determined to have violated the platform's policies. These violations include offensive reviews, fake reviews, and off-topic reviews, among others. With the two vintages of the same dataset from Google Play that we extracted six months apart, we are able to observe potential review curation behaviors. Our analysis includes 282 Android apps (38 GV apps and 244 other-VC apps) that have non-zero reviews in two snapshots we collected from Google Play in July 2023 and January 2024. We also perform similar cross-vintage comparison using the app review data of 221 iOS apps (35 GV apps and 186 other-VC apps) with non-zero reviews from the two snapshots we collected from Apple's App Store in September 2023 and September 2024.[12]

For each app, we calculate the percentage change in review volume as follows:

$$\text{Change in review volume}_{i,p,c} = \frac{\text{Review volume from the second snapshot}_{i,p,c}}{\text{Review volume from the first snapshot}_{i,p,c}} - 1 \tag{2}$$

In this equation, i indexes app, p indexes app platform, and c indexes review category. The review categories include negative reviews (rating = 1 and 2), neutral reviews (rating = 3 and 4), positive reviews (rating = 5), and bug-related reviews (bug reports). We take the average change in review volume across apps associated with different groups of VC. We include GV apps developed by startups that have not achieved an exit status as of July 2023, the date of the first data collection, to ensure that GV has an ownership tie to the developers between the two data collection dates.

During the sample period, we collected 40,027 reviews for 38 Android-version GV apps, of which 909 reviews were missing in the subsequent data collection. The 244 Android-version other-VC apps have 506,452 reviews in the first snapshot. Among these reviews, 14,909 were missing in the second snapshot. Similarly, in the iOS app review data, there are 23,825 reviews for 35 GV apps and 74,496 reviews for 186 other-VC apps in the first snapshot; 766 GV apps' reviews and 2,533 other VC apps' reviews are missing in the second snapshot.

In Figure 3, we compare the distributions of original and removed reviews across different groups and platforms to highlight the pattern in review deletions. We present four subfigures based on platform (Android and iOS) and app group (GV-backed apps and other-VC apps). Each subfigure shows consecutive bars for original reviews and removed reviews, categorized into negative reviews (1 and 2 stars), neutral reviews (3 and 4 stars), and positive reviews (5 stars).

Subfigure (b) shows that for Android apps backed by other VCs, the distribution of removed reviews closely aligns with that of original reviews, indicating a balanced and proportional pattern of review removal. However, subfigure (a) shows a different pattern for GV Android apps: while the original review distribution is similar to that of other-VC apps on the same platform, a disproportionately higher number of negative reviews are removed. Interestingly, this pattern does not extend

[12] In addition, we also collected the two-snapshot review data for 958 Android apps developed by startups backed by VCs that are connected to GV through syndication for analysis in Section 6.

to iOS apps. Subfigures (c) and (d) show that GV iOS apps do not exhibit the same disproportionate removal of negative reviews when compared to iOS apps backed by other VCs. These differences across platforms and app types underscore a significant concentration of removed negative reviews for GV apps on Google Play, suggesting a targeted pattern of review removal that could artificially enhance the perceived quality and reputation of these apps.

Figure 4 further illustrates the distribution of the negative review removal rate for GV and other-VC apps across Android and iOS platforms. The horizontal axis represents the removal rate of negative reviews, calculated as the proportion of negative reviews removed relative to the total number of initially collected negative reviews. For Android apps (subfigure (a)), the distribution of the negative review removal rate for GV apps is noticeably more left-skewed than that for other-VC apps, indicating that a higher proportion of GV apps exhibit elevated removal rates for negative reviews. In contrast, for iOS apps (subfigure (b)), GV apps show a greater concentration around a 0% removal rate relative to their Android counterparts. Complementary evidence in Table 5 reveals that 13.16% of GV Android apps have at least 10% of their negative reviews removed, significantly higher than that (3.69%) of other-VC Android apps, with the 9.47% difference being statistically significant at the 5% level. However, we see no statistically significant differences in the negative review removal rates between GV apps and other-VC apps on Apple's App Store. These findings suggest that GV-backed apps engage in more aggressive curation of negative reviews on Google Play, which is not evident on the other platform.

Table 6 presents the difference in the review removal rate between GV apps and other-VC apps on the two platforms. Our analysis focuses on reviews posted during the period from July 2022 to June 2023 for both data snapshots. We separately count three types of reviews: negative reviews (1 and 2 stars), neutral reviews (3 and 4 stars), and positive reviews (5 stars).

In Panel A, we calculate the percentage change in the number of reviews from Google Play for each type from the first snapshot in July 2023 to the second snapshot in January 2024. This analysis includes 282 apps, with 38 backed by GV and 244 backed by other VCs. Compared to other-VC apps, GV apps exhibit a larger decline in all review categories. However, the difference is statistically significant only for negative reviews and bug-related reviews. Specifically, GV apps have 5.21% of their negative reviews removed in the second snapshot, compared to 1.75% for other-VC apps. The 3.46% difference (t = -2.13) is statistically significant at the 5% level, indicating a nearly twofold higher removal rate of negative reviews for GV apps. Additionally, the Google Play platform appears to not only manage negative reviews based on star ratings but also curate review content. GV apps exhibit a 4.71% reduction in the volume of bug reports, compared to a 1.10% reduction for other-VC apps. The 3.61% difference (t = -2.48) suggests that GV apps have more than quadrupled the removal rate of bug-related reviews compared to other-VC apps. In Panel C, we repeat the analysis in Panel A but restrict the sample to Android apps with more than 20 reviews in the first snapshot to focus on more mature and widely-used applications. The results confirm our main findings, suggesting that the observed pattern of selective review filtering is not driven by apps with minimal user engagement.

Panel B presents the same analysis for iOS apps, comparing the first snapshot collected in September 2023 with the second snapshot collected in September 2024. Unlike the findings for Android apps, there are no statistically significant differences in the removal rates of negative or bug-related reviews between GV apps and other-VC apps on Apple's App Store. This contrast suggests that the differences observed on Google Play are not due to app-level characteristics but may instead reflect platform-specific review management practices, particularly on Google Play.

Since reviews can only be removed by either the original reviewer or the Google Play platform itself, and considering the lack of a clear rationale for a systematic difference in user-initiated review deletions between GV and non-GV apps, the most plausible explanation is that the Google Play platform is actively removing a higher proportion of negative reviews for GV apps. This preferential treatment in review curation has the potential to artificially inflate the perceived quality and user satisfaction of GV-backed apps, providing them with an unfair advantage in the highly competitive app market.

One potential alternative explanation for this observed curating pattern is that GV apps may somehow feature a higher proportion of inappropriate reviews that violate Google Play's policies and thus induce more platform removals. To investigate this possibility, we develop a neural network algorithm to analyze the semantic differences between the removed reviews and those that remained. Specifically, we construct a balanced training sample of 678 negative reviews from GV apps on Google Play, comprising all 339 removed negative reviews and 339 randomly selected retained negative reviews. We utilize the BERT (Bidirectional Encoder Representations from Transformers) model to process the review texts and use the processed outcomes as model inputs. Then, we construct a 4-layer neural network to check if the algorithm could distinguish the removed reviews based solely on the content.[13] The accuracy, precision, and recall rates of the model are 52%, 52%, and 54%, respectively, close to the rates expected from a random draw. These results indicate that there is little semantic difference between the removed negative reviews and the unremoved negative reviews, at least to the extent that our deep learning model can detect. This pattern is inconsistent with the platform removing more inappropriate content from GV-apps' reviews.

To further examine potential semantic differences, we apply similar techniques to compare removed negative reviews from GV apps with those from other-VC apps from Google Play. For this analysis, we construct a balanced dataset of 4,160 removed negative reviews and 4,160 randomly chosen retained negative reviews from other-VC apps, covering the same period (July 2022 to June 2023). We use 80% of this dataset as a training set to train the model and the remaining 20% as a validation set for out-of-sample testing. During the training stage, we use the BERT model to process the review texts, which were then analyzed using the same four-layer neural network. We then use the model trained and validated using other VC apps' reviews to predict the removal of GV apps' reviews. Table 7 presents the model performance across different datasets. On the training set of other-VC app reviews, the model achieved an accuracy of 65%, precision of 75%, and recall of 46%. On the validation set of other-VC reviews, the model's performance was nearly identical, with 64% accuracy, 74% precision, and 44% recall, indicating consistent criteria for review removal across other-VC apps. However, when the model was tested on the GV app dataset, its performance dropped significantly, achieving 54% accuracy, 60% precision, and 24% recall. This performance gap suggests that the criteria used to remove negative reviews from GV apps may differ substantially from those applied to other-VC apps, reinforcing the possibility of preferential curation for GV apps on Google Play.

4 Consequences of platform intervention

The previous section provides evidence consistent with the two channels, visibility enhancement and review curation, through which GV offers preferential treatment to the apps developed by their investees through the Google Play platform. These preferential treatments could lead to greater success for the startups' Android apps, especially compared to their iOS apps where such preferential treat-

[13] 1 input layer, 1 hidden layer with ReLU activation function, 1 hidden dropout layer, 1 output layer with sigmoid activation function, consecutively.

ment is absent. For example, platform promotion through frequent suggestions of "similar apps" may enhance the apps' download and usage. The selective removal of negative and bug-related reviews could lead to artificially inflated ratings and higher perceived quality. These effects could lead to an additional increase in subsequent ratings and usage volume. Note that the review truncation we observe only occurs within the 6-month period between the two snapshots, and thus, our estimates likely understate the true degree of review curation.

To assess the long-term effect of the preferential treatment GV provides to its portfolio firms through the Google Play platform, we conduct a Difference-in-Differences (DiD) analysis using the firms' Android apps as the treatment group and their iOS counterparts as the control group. The Android and iOS versions of the same app typically offer identical functionalities and cater to similar-sized user bases, making the iOS version an ideal control group for this analysis. This approach allows us to evaluate the effect of GV's investments on the performance of its investees' Android apps.

Previous research in the VC literature often employs DiD analysis using alternative startups as the control group (e.g., Bernstein et al., 2016; Chemmanur et al., 2014). However, it is challenging for this approach to distinguish the treatment effects of VC investment from their selection effects, i.e., VCs' superior ability to identify and invest in promising startups ex-ante. By comparing the two versions of the same app, our DiD design effectively isolates the treatment effects from the selection effects because any selection effects would manifest at the startup level and influence both the Android and iOS versions of the app. Consequently, our approach provides a more precise estimation of the effect of GV's preferential treatment on the performance of its portfolio firms' apps, while minimizing potential confounding factors.

We estimate the following DiD regression for the apps developed by GV-invested startups:

$$\begin{aligned} \text{Performance}_{i,j,v,q} =& \beta_0 + \beta_1 \text{Android app}_{i,j,v} + \beta_2 \text{Post}_{i,q} \\ & + \beta_3 \text{Post}_{i,q} \times \text{Android app}_{i,j,v} + \beta_4 X_{i,j,q} + \epsilon_{i,j,q} \end{aligned} \tag{3}$$

The dependent variable, $\text{Performance}_{i,j,v,q}$, denotes various app performance metrics (see Section 2.3) for startup i, app pair j (i.e., each pair consists of the Android and the iOS version), app version v (i.e., Android or iOS), and calendar quarter q. $\textit{Android app}_{i,j,v}$ is a binary variable that equals one for the Android version of the apps, and zero for the iOS versions. $\textit{Post}_{i,q}$ is a binary variable that equals one for quarters after GV's investment in startup i. The control variables, denoted by $X_{i,j,q}$, include alternative combinations of the following fixed effects: app pair fixed effects, quarter fixed effects, and app pair $\times$ quarter fixed effects. The inclusion of app pair $\times$ quarter fixed effects ensures the most direct comparison between the two versions of the same app pair during the same period. To ensure sufficient observations for the pre-investment periods, we include an app pair in the sample only if both its Android and iOS versions were launched at least two quarters before GV's investment. The final sample consists of 1,494 app-quarter observations from January 2010 to June 2023 for 22 app pairs developed by 17 startups that were backed by GV during that period. We estimate the standard errors with app pair clustering.

4.1 Review volume of Android apps

The volume of app reviews serves as an indicator of an app's popularity, reflecting both the size of the user base and the degree of user engagement. This metric is crucial for determining the cash flow and valuation of startups, playing a pivotal role in their survival and success. Since the Android version of GV apps uniquely benefits from Google Play's promotion and review curation, as suggested in Section 3, these preferential treatments could lead to greater increases in the affected Android apps' download and usage, which can be reflected by enhancements in review volume.

Table 8 reports the estimates of Model (3) using *Log(review volume)* as the dependent variable and alternative combinations of fixed effects. The coefficient for *Post* is uniformly positive and statistically significant in columns 1 and 2, indicating that the popularity of both versions of GV apps improved after GV's investments. Importantly, the coefficient for the interaction term, *Post* $\times$ *Android app*, is consistently positive and statistically significant at the 1% level across models. For instance, the estimates in column 3, in which we control for app pair $\times$ quarter fixed effects to achieve a within-app-pair-quarter comparison, suggest that the Android version of GV apps experienced an additional increase in review volume by 115% (i.e., $e^{0.765} - 1$) relative to the iOS counterparts after GV's investments. These results support the hypothesis that the promotion of GV apps on Google Play could enhance the popularity of their Android version relative to their iOS version.[14]

[14]To address potential concerns regarding the use of the log of one plus the number of reviews as the dependent variable, as pointed out by Cohn et al. (2022), we alternatively estimate Poisson regressions with the number of reviews as the dependent variable. Both the magnitude and the significance of the coefficient estimates on the interaction term are consistent with those reported in Table 8, supporting the robustness of our findings.

To test the parallel-trend assumptions and observe the timing of the uptick in the affected Android apps' review volume, we estimate the dynamic version of Model (3). Specifically, we follow the specification in column 3 of Table 8, but decompose the interaction term *Post* $\times$ *Android app* into the interactions between *Android app* and all the event quarter indicators in the sample period. Figure 5 presents the estimates for the interaction terms from 8 quarters before to 28 quarters after GV's investment, with quarter -1 set as the base group. The figure indicates that the trends of review volume for the app pairs appear parallel before GV investment. After that, the review volume of the Android apps trends upward relative to the iOS counterparts over time. These results are consistent with the parallel trends assumption of our DiD models.

We also examine whether the GV's treatment effect is related to its investment stake and long-term commitment by estimating an alternative specification where we replace the *Post* dummy with the cumulative number of financing rounds (*# Rounds*), which increments each time the startup raises additional funding from GV. In this alternative specification (available upon request), the coefficient for *# Rounds* $\times$ *Android app* is positive and statistically significant at the 5% level for review volume. This result indicates that the treatment effect on review volume becomes stronger as GV increases its cumulative investment in the startup.

4.2 Review rating of Android apps

The review rating serves as a critical indicator of app user satisfaction, which could shape future user demand and firm revenue (Huang, 2018). The disproportionate removal of negative reviews by Google Play could result in inflated ratings for the affected Android apps compared to their iOS counterparts. To examine this conjecture, we estimate Model (3) using *Mean rating* as the dependent variable.

Table 9 reports these estimates with different sets of fixed effects, similar to Table 8. The sample includes 1,392 app-quarter observations that have non-zero number of reviews. The coefficient for the interaction term *Post* $\times$ *Android app* is consistently positive and statistically significant across specifications, indicating a tangible benefit of GV investment on the rating of the Android version of GV apps. Notably, the estimates in column 3, where we include app pair $\times$ quarter fixed effects in the regression, suggest that after GV's investment, the Android version of GV apps experienced a significant increase in mean rating of 0.452 relative to their iOS counterparts. This increment represents approximately 12.3% of the average mean rating for Android apps (3.663), highlighting the significant influence of GV in enhancing the ratings of its portfolio firms' Android apps.

Figure 6 presents the estimates for the dynamic version of Model (3) for mean rating, following the specification in column 3 of Table 9. The figure indicates that the pre-trends appear parallel before GV's investment. Afterward, the mean rating of GV firms' Android apps steadily increases relative to their iOS counterparts. Eventually, the difference in rating between the Android and iOS versions significantly exceeds that in the pre-treatment period. The pattern in Figure 6 is consistent with the parallel trends assumption of our DiD models.

4.3 Bug reports of Android apps

A bug report is one of the key pieces of information that can be extracted from review content, specifically reflecting the technical quality of an app. Detecting bug reports and debugging in a timely manner is one of the most important tasks for app developers (Liu et al., 2014). However, the disproportionate removal of bug-related reviews from Google Play could lead to a lower rate of bug reports and higher perceived quality for the Android version of GV apps compared to their iOS counterparts.

In Table 10, we present the estimates of Model (3) using the proportion of reviews that mention bug-related keywords (*%Bug*) as the dependent variable. The sample includes 1,392 app-quarter observations that have non-zero number of reviews. The estimates reveal that the coefficient for the interaction term *Post* × *Android app* is consistently negative and statistically significant. Specifically, column 3 indicates that following GV's investment, the affected Android apps see a significant decrease in the *%Bug* metric by 3.4 percentage points relative to their iOS counterparts. This reduction constitutes approximately 77.3% of the average *%Bug* for Android apps (4.4 percentage points), signaling a substantial decrease in complaints related to the technical quality of the Android apps following GV investment.

Figure 7 presents the estimates for the dynamic version of Model (3) for *%Bug*, following the specification in column 3 of Table 10. The figure reveals an immediate downward shift in the proportion of bug-related reviews for the treated Android apps relative to their iOS counterparts after GV's investments. This pattern is again consistent with the parallel trends assumption of our DiD models.

4.4 Benchmarking GV treatment effects against other investing entities

The analysis in Sections 4.1 to 4.3 suggests significant treatment effects of GV investment on the performance of the affected Android apps in terms of review volume, rating, and perceived technical quality as reflected by the proportion of bug-related reviews. The assumption underlying this empirical design is that the performance of the Android version of an app should align with that of its iOS counterpart, except when it receives asymmetric preferential treatments conferred by GV. Therefore, we should not observe the same treatment effects from other VCs on their portfolio firms' Android apps if they cannot provide similar preferential treatments on Google Play as GV does.

To formally test this assumption, we repeat the same treatment effect estimation using all the other VCs in our sample. We include 127 VCs other than GV that have each invested in a minimum of five startups with apps that have both versions launched at least two quarters prior to the quarter of the VC investment. Additionally, the apps associated with GV are excluded from the sample apps for other VCs to isolate GV treatment effects from those of other VCs. We perform the same DiD analysis following the setting of column 3 across Tables 8, 9, and 10, using VC investment as the treatment event for each of these 127 VCs. Using the t-statistics of the DiD estimators as the basis of comparison, we obtain the percentile rank of the estimated treatment effect on the three performance metrics for all 128 VCs (including GV). We then calculate the total treatment rank for each VC based on the sum of the three treatment percentiles.[15]

Figure 8 provides a visual representation of the percentile rankings of treatment effects for each VC across the three metrics. GV ranks in the 91st percentile for volume treatment effects, the 90th percentile for rating treatment effects, and the 98th percentile for bug-reduction treatment effects. As for the overall treatment rank, GV ranks at the top among all 128 VCs. Thus, the estimated treatment effects of GV on its portfolio firms' Android apps stand out from those of other VCs. This evidence supports our identification assumption and our causal interpretation of the estimates in Tables 8 to 10.

[15] Since a negative treatment effect on *%Bug* indicates an improvement in app quality, we rank the treatment effect on *%Bug* based on 1 minus the percentile.

4.5 Alternative explanation: Intrinsic quality improvement

Thus far, we have contended that the observed GV treatment effects likely stem from the preferential promotion and curated reviews that GV apps enjoy on the Google Play platform. However, an alternative explanation merits consideration: the treatment effects may be attributable to the technical guidance provided by GV, which could potentially enhance the quality and popularity of the Android apps under its purview. Given Google's role in designing the Android operating system, it is reasonable to presume that GV possesses specialized expertise in Android app development.

If the Android apps under GV's guidance do indeed undergo quality improvements, these enhancements should manifest through periodic app updates, which are crucial for addressing bugs, bolstering security, and introducing new features. Therefore, if this alternative explanation holds true, we should expect to observe a more pronounced GV treatment effect on review volume, rating, and bug reports in conjunction with app updates. To investigate this potential alternative mechanism, we re-estimate Model (3) by adding a triple interaction between the post-GV-investment indicator, the Android app indicator, and the app update frequency as follows:

$$\begin{aligned}
\text{Performance}_{i,j,v,q} =& \beta_0 + \beta_1 \text{Android app}_{i,j,v} + \beta_2 \text{Update frequency}_{i,j,v,q-1} \\
&+ \beta_3 \text{Post}_{i,q} \times \text{Android app}_{i,j,v} \\
&+ \beta_4 \text{Android app}_{i,j,v} \times \text{Update frequency}_{i,j,v,q-1} \\
&+ \beta_5 \text{Post}_{i,q} \times \text{Update frequency}_{i,j,v,q-1} \\
&+ \beta_6 \text{Post}_{i,q} \times \text{Android app}_{i,j,v} \times \text{Update frequency}_{i,j,v,q-1} \\
&+ \beta_7 X_{i,j,q} + \epsilon_{i,j,q}
\end{aligned} \tag{4}$$

Update frequency$_{i,j,v,q-1}$ is the frequency of updates for each app version in the previous quarter. If GV indeed enhances its investees' Android apps' quality and popularity through app updates, the coefficient for the triple interaction term should be significantly positive for review volume and rating and significantly negative for bug reports. The coefficient for *Post* $\times$ *Android app* would indicate the GV treatment effect for the treated apps with zero update.

Table 11 presents the estimates of Model (4) for the three performance metrics. Contrary to the prediction for this alternative mechanism, the coefficient for the triple interaction term is not significantly different from zero for all three performance metrics and has the opposite sign to the predicted treatment effect. Moreover, the coefficient for *Post* × *Android app* remains significantly positive for review volume and significantly negative for bug reports after adding the triple interaction term, suggesting that the enhanced perceived quality and popularity of the apps happened precisely when the apps were *not* updated (i.e., where *Update frequency*=0). Although the coefficient for *Post* × *Android app* is not statistically significant for app rating, its magnitude is close to that in the baseline model in Table 9.

The GV treatment effect's insensitivity to app updates persists across alternative specifications. In additional tests (available upon request), we find consistent results, whether measuring updates contemporaneously or cumulatively since the app's release. While we recognize that update frequency isn't necessarily a perfect quality indicator—as updates range from minor fixes to major overhauls—any meaningful quality improvement through technical expertise would typically involve at least one update. To explore this further, we replaced the continuous *Update frequency* measure with a simple binary indicator of whether an app received any updates. Even with this approach, we find that the triple interaction term remains statistically insignificant and does not explain the effect of the GV treatment. Therefore, our findings suggest that intrinsic quality improvements through technical upgrades are unlikely to drive the observed performance gains for GV-backed apps.

5 GV investment and startup success

We next examine the association between GV's ownership and the long-term outcomes of the app-developing startups.

5.1 Startup financing outcome

Table 12 presents the financing outcomes for startups affiliated with GV and other VCs during the sample period. Overall, GV-invested startups exhibit more favorable financing outcomes. Specifically, GV-invested startups participate in an average of 5.95 funding rounds, which is 3.28 rounds more than those financed by other VCs, a difference statistically significant at the 1% level. These startups also secure a cumulative average financing of $639.46 million, in contrast to the $30.29 million accrued by startups backed by other VCs, with this difference also significant at the 5% level. Moreover, on a per-round basis, GV-invested startups receive an average of \$72.86 million, compared to \$11.16 million for startups associated with other VCs, a difference significant at the 1% level.

Has the superior performance of GV apps contributed to better financing outcomes for GV-invested startups? To shed light on this question, we construct a startup-year panel dataset, pairing each startup with its most downloaded app on Google Play. Then, we estimate the following regression to examine the correlation between app performance and firm financing outcomes:

$$\begin{aligned}\text{Financing outcome}_{i,t+1} =& \beta_0 + \beta_1 \Delta \text{Log(review volume)}_{i,t} + \beta_2 \Delta \text{Mean rating}_{i,t} \\ &+ \Delta\%\text{Bug}_{i,t} + \epsilon_{i,t}\end{aligned} \tag{5}$$

The dependent variable, *Financing outcome*$_{i,t+1}$, denotes various measures of financing outcome for startup i in year $t+1$. Δ*Log(review volume)*$_{i,t}$ is the change in the natural logarithm of one plus the yearly review volume from year $t-1$ to year t. Similarly, Δ*Mean rating*$_{i,t}$ and Δ*%Bug*$_{i,t}$ are the yearly differences in *Mean rating* and *%Bug*. We measure firms' financing outcomes in two ways: $I_{Funding}$, a binary indicator that equals one if the startup obtained any equity financing in the subsequent year; and *Log(Total funding)*, the natural logarithm of one plus the total financing amount raised by the startup in the subsequent year. We utilize these two measures to assess the correlation between changes in app performance metrics and the likelihood and the amount of financing.

Table 13 indicates a significant correlation between app performance metrics and future financing success. Specifically, a 10% increase in the growth of review volume is associated with a 0.17 percentage-point increase (i.e., $ln(1+10\%) \times 0.018$, or 0.7% of the sample mean, 23.65 percentage points) in the probability of obtaining financing in the subsequent year and a 0.9% (i.e., $e^{(ln(1+10\%)\times 0.09)}-1$) increase in the total financing amount secured in that period. Moreover, a one-unit increase in the mean rating correlates with a 1.3 percentage-point increase (or 5.5% of the sample mean) in the probability of securing financing in the following year and a 4.3% increase in the total amount of financing. The number of bug-related reviews, however, does not exhibit a significant direct correlation with financing outcomes.

While the perceived technical quality of an app may not directly translate into better financing outcomes, it might indirectly contribute to firms' financing by boosting future user downloads and usage. This evidence is also consistent with our earlier analysis, which suggests that GV might have taken deliberate actions to delete the negative and bug-related ratings for the apps developed by their investees and that these apps are associated with higher review volume after GV's investments. To examine this possibility, in column 3 of Table 13, we examine the correlation between changes in the app's rating and bug reports and future app review volume while controlling for current changes in review volume. The estimates suggest that improvements in current rating and bug reports are significantly predictive of future review volume, suggesting higher future user downloads and usage. These correlations are consistent with our conjecture that platform curation of the review data might have contributed to favorable financial outcomes either directly or indirectly by boosting future user demand.

5.2 Startup exit outcome

Table 14 reports the exit outcomes for the startups in the sample. By the end of 2023, 26.19% of GV-invested startups have achieved a successful exit, among which 11.90% have successfully completed an initial public offering (IPO).[16] Both of these numbers exceed those for startups associated with the other VCs, though the differences are not statistically significant.

The results in Tables 12 to 14 all point to a significant association between GV ownership and the long-term success of app-developing startups. While these results do not account for potential endogeneity, such as GV's superior startup selection skills, they are consistent with our evidence that GV plays a proactive role in boosting its investees' app performance on its own platform and suggests the tangible benefits of their intervention. These tangible benefits further justify GV's motivation to promote its invested apps using its market power in the mobile app market.

6 Extending preferential platform treatment to investment partners

Evidence in Section 3 indicates that GV-backed apps receive preferential support from the Google Play platform, boosting their visibility and perceived quality. Along these lines, it is plausible that VCs with established connections to GV also derive benefits from the platform, given the existing evidence of the value of VC networks (Hochberg et al., 2007; Sorenson and Stuart, 2001). To examine

[16] Successful exit events include mergers, IPOs, secondary sales, direct public offerings, write-offs, buybacks, and reverse takeovers.

this possibility, we extend the analysis in Table 2 and Table 6 to apps associated with VCs that are connected with GV through previous syndication (referred to as connected-VC hereafter).

Panel A of Table 15 presents the difference in app visibility between connected-VC apps and other-VC apps on Google Play, following the methodology in Table 2. Connected-VC apps are recommended as similar apps an average of 15.08 times. Of these recommendations, 7.50 times are from apps within the same genre, while 7.58 times come from apps across different genres. Moreover, these apps are recommended by apps from 2.20 different genres on average. Additionally, connected-VC apps display significantly higher visibility across all these dimensions compared to other-VC apps. However, their advantage in visibility over other-VC apps is smaller in magnitude compared to GV apps, as shown in Table 2.

Panel B of Table 15 presents the difference in the review removal rate between connected-VC apps and other-VC apps from Google Play, following the methodology outlined in Panel A of Table 6. The results show that 2.69% of negative reviews for connected-VC apps were removed in the second snapshot, compared to 1.75% for other-VC apps. The difference of -0.95% (t = -2.78) is statistically significant at the 1% level, suggesting potential review curation for apps backed by connected VCs. Similarly, connected-VC apps exhibit a 2.06% reduction in the volume of bug reports, compared to a 1.10% reduction for other-VC apps, with the difference statistically significant at the 1% level. However, the removal rates of negative and bug-related reviews for connected-VC apps are less pronounced than those observed for GV apps, as reported in Panel A of Table 6.

These results are collectively consistent with the notion that preferential support from the platform might extend to VCs with established connections to the platform owner, albeit to a lesser degree than that enjoyed by GV apps. This evidence lends additional credence to the benefits of syndication networks and highlights the potential advantages of having strong ties to the platform owner.

7 Conclusion

The rising dominance of superplatforms raises concerns about conflicts of interest and potential externalities on innovation and entrepreneurship, as they simultaneously act as marketplace gatekeepers and strategic investors. We investigate the influence of platform-backed venture capitalists on their portfolio companies, focusing on Google Ventures (GV) and its connection to Google Play. By comparing the same mobile apps across Google Play and Apple's App Store, we find compelling evidence that following GV's investment, startups' Android apps experience a 115% increase in review volume, a 12% rise in average rating, and a 77% reduction in bug-related reviews compared to their iOS counterparts. Notably, these improvements occur independently of app updates, suggesting they stem not from intrinsic quality enhancements via GV's technical guidance but rather from preferential platform treatment.

Our investigation reveals two key mechanisms driving these advantages. First, GV-backed apps gain substantially more visibility through frequent "similar apps" recommendations on Google Play. Second, analysis of review data collected in July 2023 and January 2024 (covering July 2022 to June 2023) demonstrates that negative and bug-related reviews are disproportionately removed for GV-backed Android apps, artificially inflating their ratings. These practices exemplify "self-preferencing" behaviors, where platforms favor affiliated entities over competitors. Unlike Cunningham et al. (2021), who identify "killer acquisitions" where incumbents completely eliminate competition by purchasing and discontinuing innovative projects, our findings highlight a more subtle yet potentially more pervasive strategy: platforms can systematically advantage their investment portfolio companies through algorithmic promotion and content moderation without requiring outright acquisition. This approach allows platforms to maintain the appearance of market neutrality while still tilting competitive dynamics in favor of their financial interests, creating what might be termed "cultivated advantages" rather than eliminated competition.

Our findings align with broader regulatory concerns about platform self-preferencing. In a landmark 2022 ruling, the EU General Court upheld a €4.125 billion fine against Google for using its Android platform to strengthen its market position in web search (Paemen et al., 2022). Like the Android case, which highlighted Google's ability to leverage platform control, we find evidence that Google Ventures uses the Google Play platform to provide advantages to its portfolio companies through both promotional visibility and selective content moderation. Under current U.S. antitrust law, self-preferencing is prohibited only if the firm possesses substantial market power in the relevant goods sector and if competitive harm emerges due to unequal treatment (Hovenkamp, 2023). The systematic advantages we document highlight critical structural vulnerabilities in platform-mediated markets, where integrated ownership structures create potent channels for strategic market manipulation. By demonstrating how ownership interconnections enable systematic influence over competitive dynamics, we uncover fundamental challenges to market neutrality that extend far beyond the specific context of digital ecosystems and raise questions about regulatory frameworks for platforms that simultaneously serve as market referees and strategic investors.

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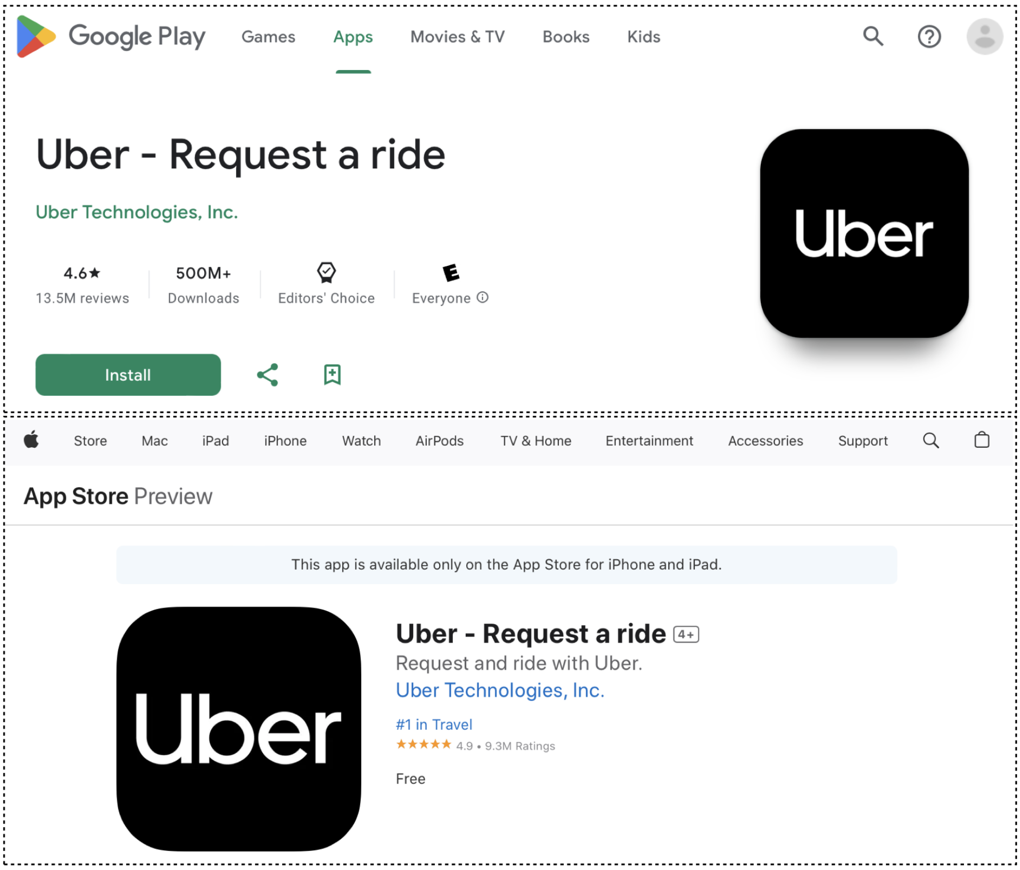
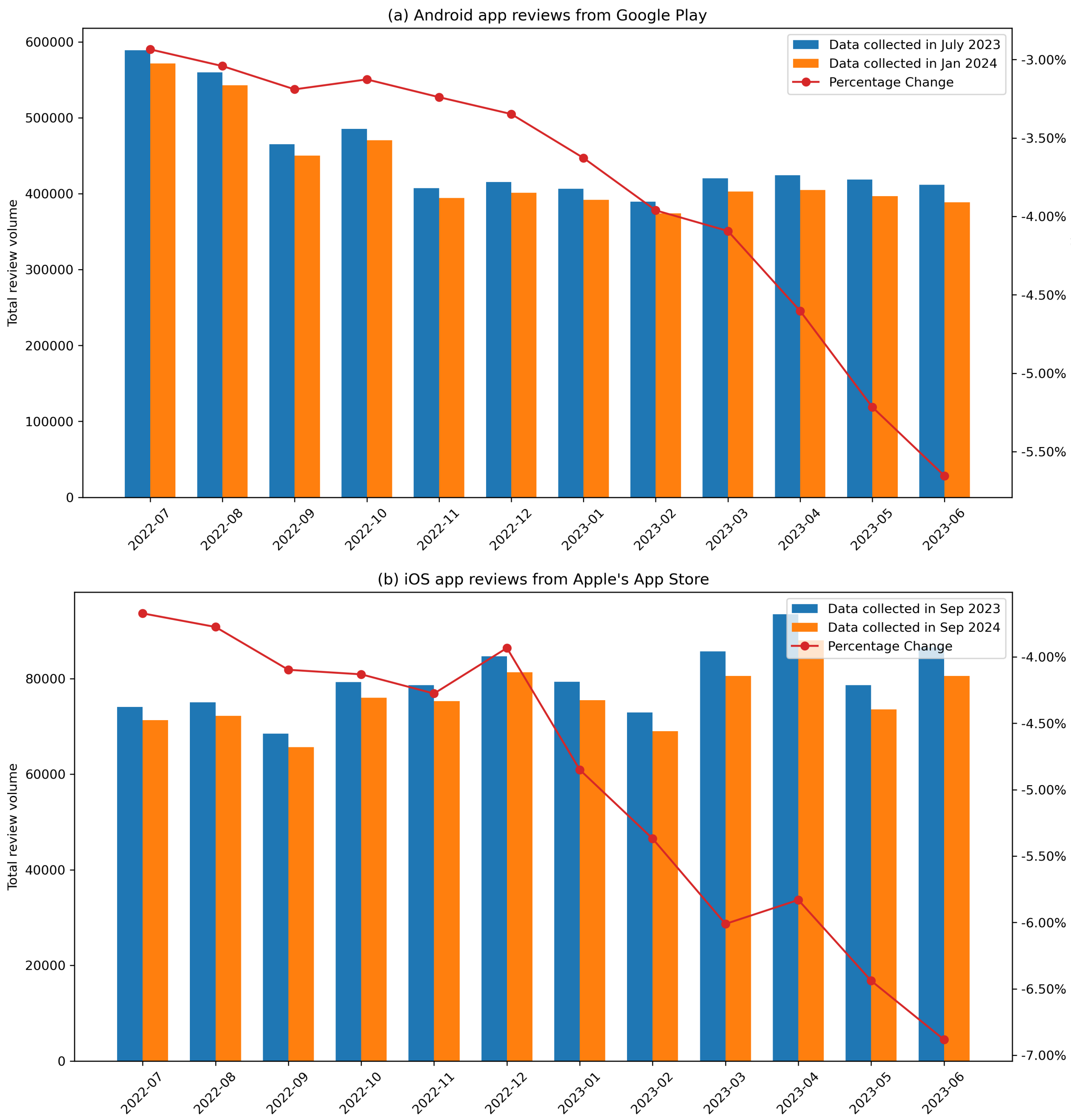
Figure 1: Uber app on Google Play and Apple's App Store



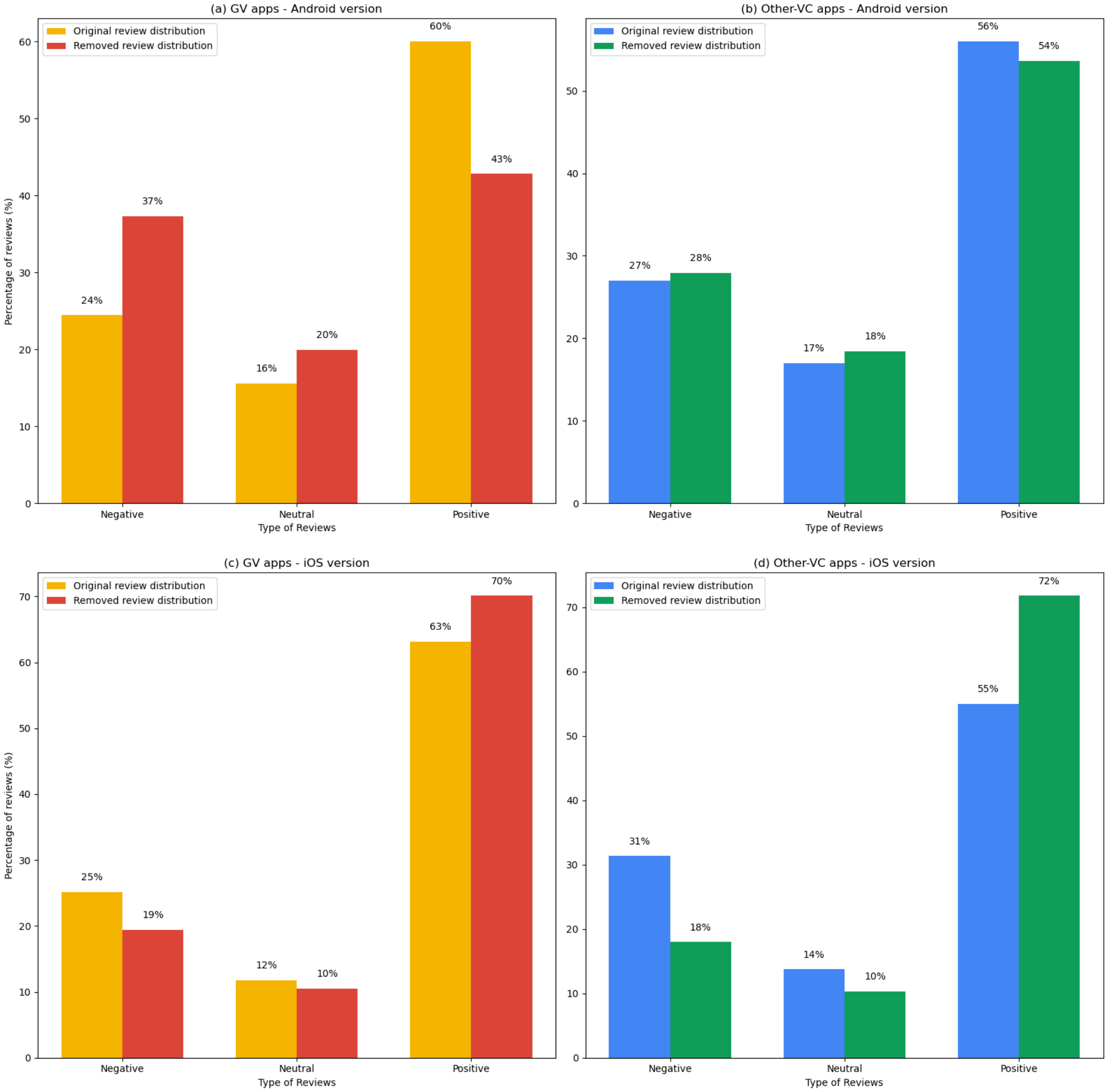
This figure provides an example of an app pair. The above is the Android version of the Uber app on Google Play. The bottom is the iOS version of the Uber app on Apple's App Store.

Figure 2: Monthly total app review volume across two data snapshots



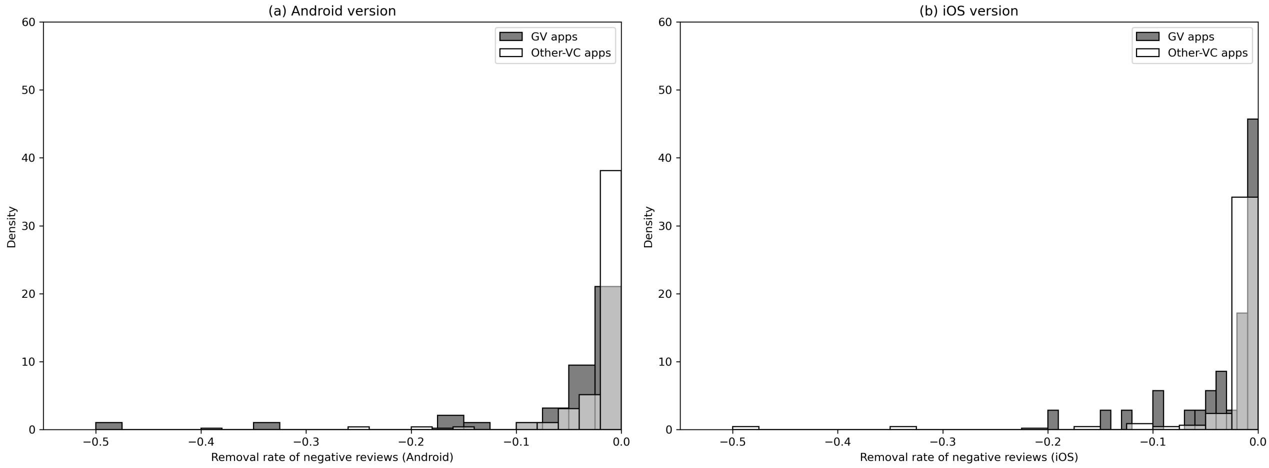
This figure shows the monthly total app review volume from July 2022 to June 2023. Subfigures (a) and (b) show the review trends for Android apps from Google Play and iOS apps from Apple's App Store. The blue bars represent the review volume from the first snapshot (July 2023 for Google Play and September 2023 for Apple's App Store); the orange bars represent the review volume from the second snapshot (January 2024 for Google Play and September 2024 for Apple's App Store). The red line indicates the percentage change in monthly review volume from the first to the second snapshot for each platform. To address concerns about potentially incomplete data, we include only apps with non-zero reviews in both snapshots for the analysis.

Figure 3: The distributions of original reviews and removed reviews



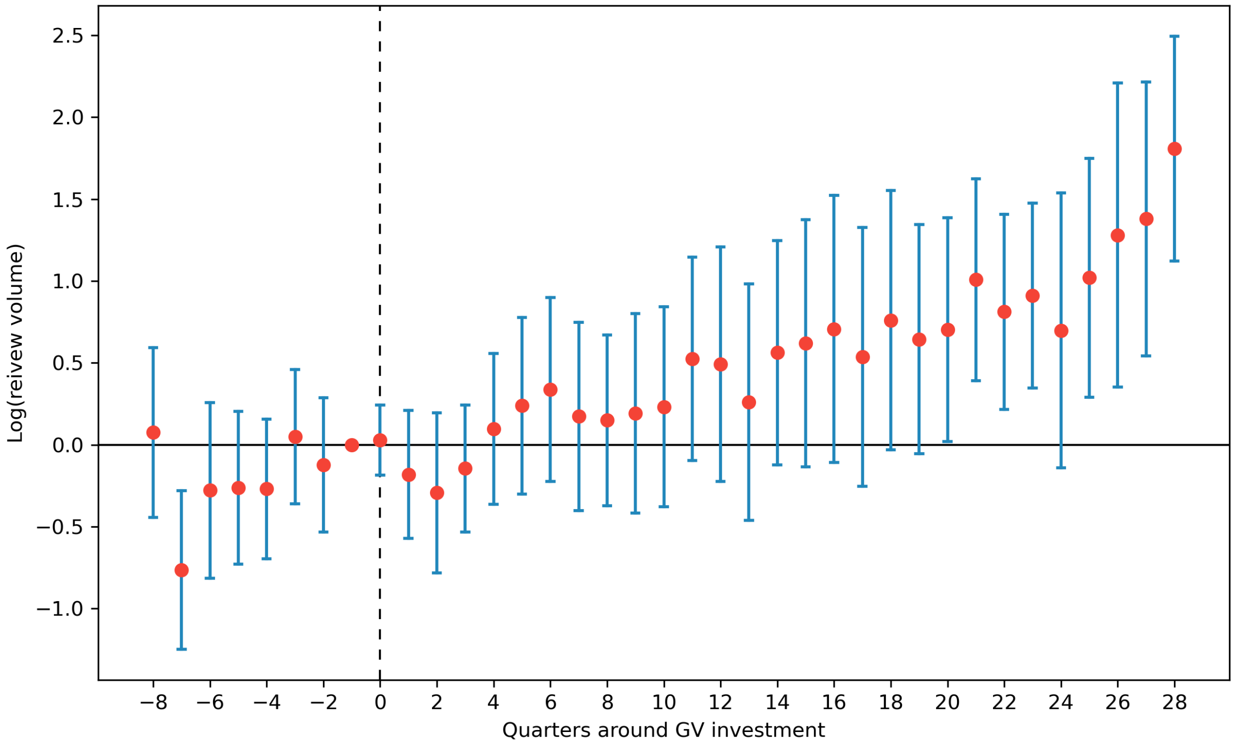
This figure displays the distribution of original reviews from the initial data collection and the distribution of removed reviews identified by comparing the initial to the subsequent data collection for each platform. Subfigures (a) and (b) present the distributions for Android apps from Google Play; subfigures (c) and (d) present the distributions for iOS apps from Apple's App Store. In subfigures (a) and (c), the yellow and red bars correspond to the distributions of the original and removed reviews for GV-backed apps; in subfigures (b) and (d), the blue and green bars represent the distributions of the original and removed reviews for apps backed by other VCs that have not co-invested with GV. The numbers above the bars indicate the proportion of each review type—negative, neutral, and positive—within the respective categories.

Figure 4: The distribution of the removal rate of negative reviews



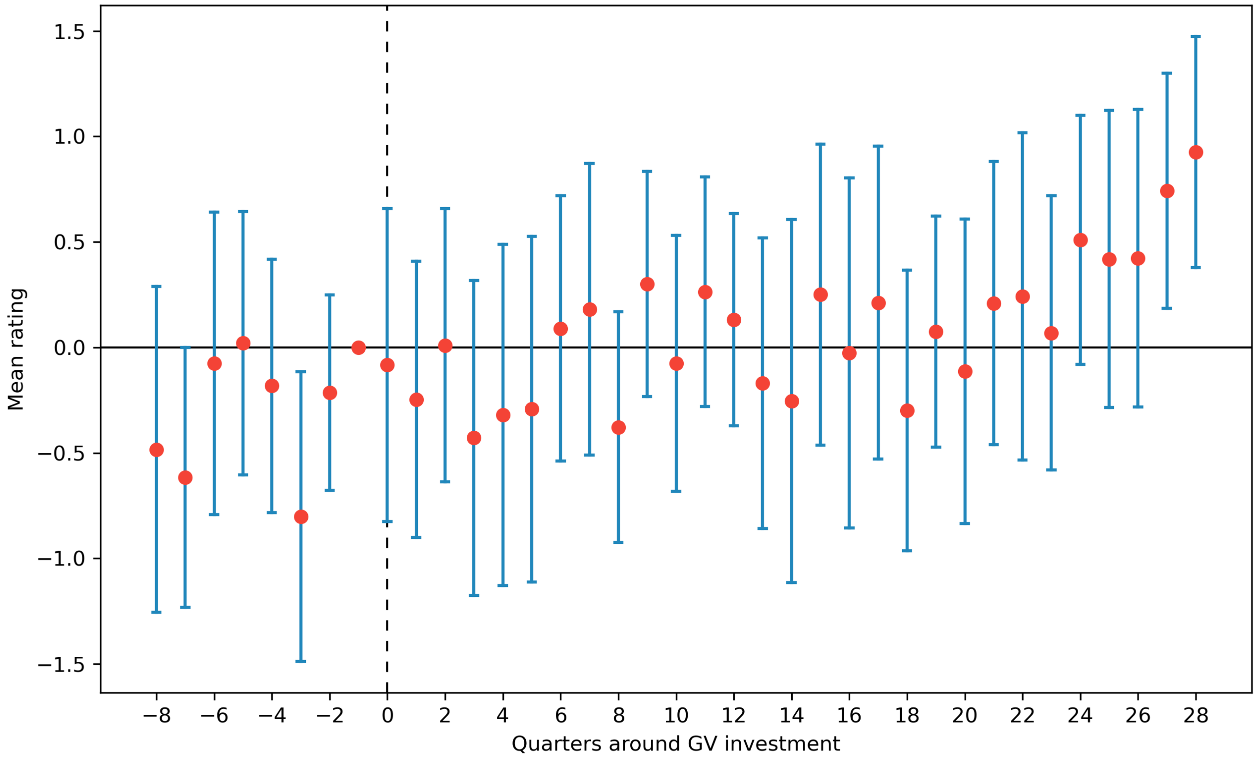
This figure presents the density histogram of the removal rate of negative reviews for each platform. Negative reviews refer to reviews with 1 and 2-star ratings. The removal rate for each app is calculated as the relative change in the total number of negative reviews between the two review data snapshots for the same period from July 2022 to June 2023. Subfigure (a) shows the distribution for 38 Android-version GV apps (black bars) and 244 Android-version apps backed by other VCs (white bars). Subfigure (b) shows the distribution for 35 iOS-version GV apps (black bars) and 186 iOS-version apps backed by other VCs (white bars). *GV app* refers to apps developed by startups backed by GV and without an exit status as of July 2023, ensuring GV's ownership during the data collection period. *Other-VC app* refers to apps developed by startups backed by VCs that have never co-invested with GV.

Figure 5: The difference in review volume between Android and iOS apps around GV investment



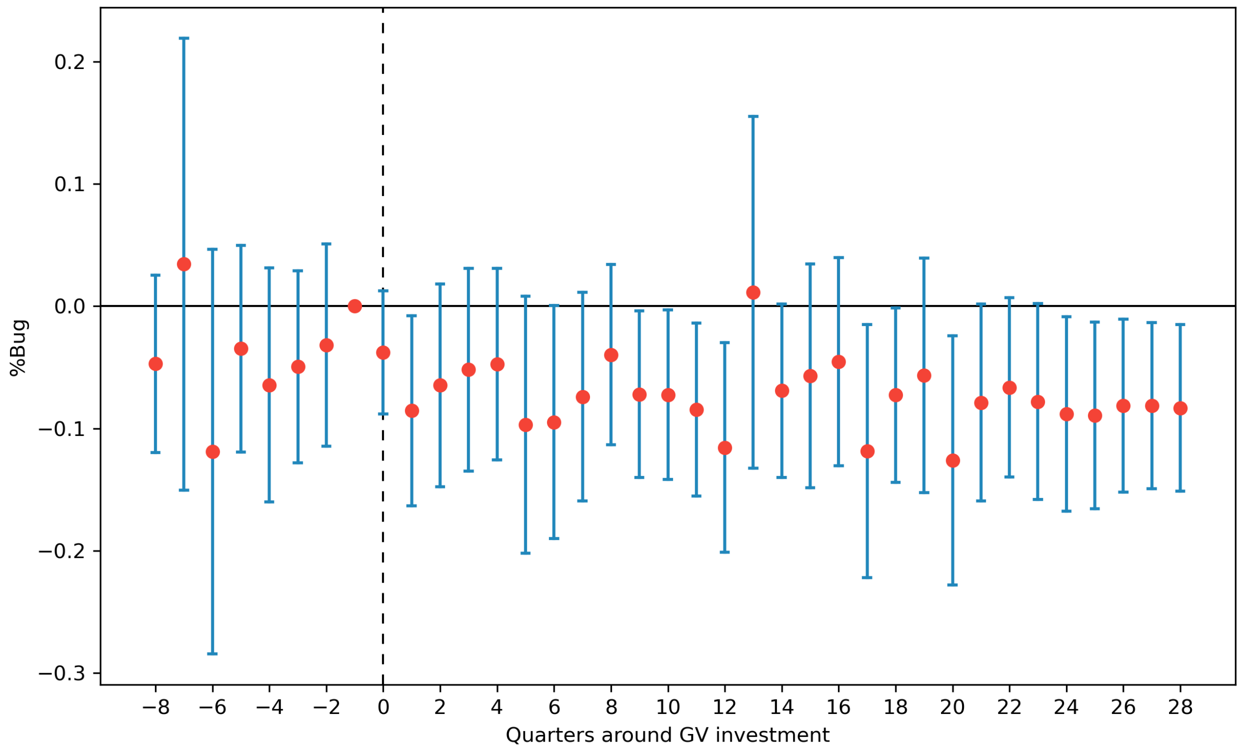
The figure shows the coefficient estimates of the dynamic version of Model (3) with *Log(review volume)* as the dependent variable, following the specification in column 3 of Table 8. The horizontal axis refers to quarters from 8 quarters before to 28 quarters after the investment of GV. Each node represents the coefficient estimate for the interaction between *Android app* and the corresponding quarter indicator around the treatment effect, i.e., GV investment. The cap spike denotes the 95% confidence interval of the coefficient estimates. The coefficient on *Android app* × *Quarter(-1)* is set as the baseline in the regression.

Figure 6: The difference in mean rating between Android and iOS apps around GV investment



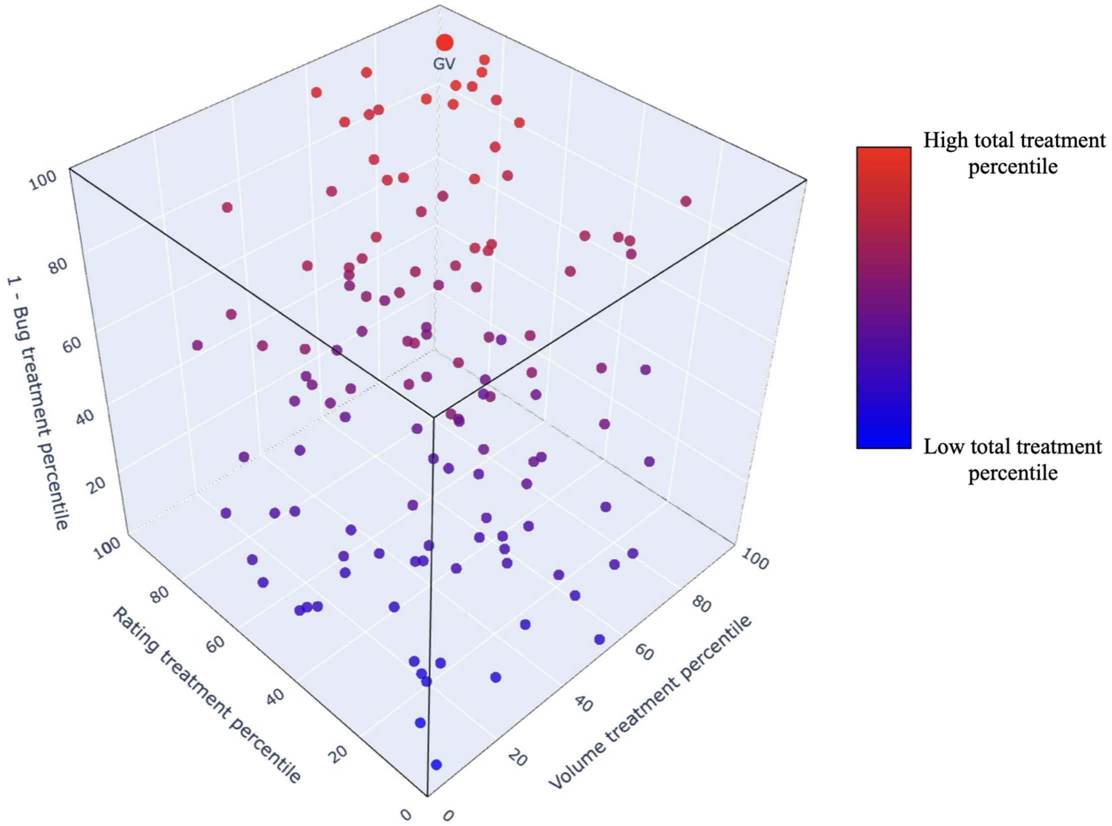
The figure shows the coefficient estimates of the dynamic version of Model (3) with *Mean rating* as the dependent variable, following the specification in column 3 of Table 9. The horizontal axis refers to quarters from 8 quarters before to 28 quarters after the investment of GV. Each node represents the coefficient estimate for the interaction between *Android app* and the corresponding quarter indicator around the treatment effect, i.e., GV investment. The cap spike denotes the 95% confidence interval of the coefficient estimates. The coefficient on *Android app* × *Quarter(-1)* is set as the baseline in the regression.

Figure 7: The difference in bug reports between Android and iOS apps around GV investment



The figure shows the coefficient estimates of the dynamic version of Model (3) with *%Bug* as the dependent variable, following the specification in column 3 of Table 10. The horizontal axis refers to quarters from 8 quarters before to 28 quarters after the investment of GV. Each node represents the coefficient estimate for the interaction between *Android app* and the corresponding quarter indicator around the treatment effect, i.e., GV investment. The cap spike denotes the 95% confidence interval of the coefficient estimates. The coefficient on *Android app* × *Quarter(-1)* is set as the baseline in the regression.

Figure 8: Comparative ranking of GV treatment effects



This figure plots the percentile ranking of VC treatment effects for all the 128 VCs (including GV) that have invested in a minimum of five startups included in the sample. We estimate the same DiD regressions for each of the 128 VCs, following the specification of column 3 of Tables 8, 9, and 10. The volume treatment effect percentile is based on the ranking of t-statistics for the interaction term *Post* × *Android app*, with *Log(review volume)* as the dependent variable. The rating treatment effect percentile is based on the ranking of t-statistics for the interaction term *Post* × *Android app*, with *Mean rating* as the dependent variable. The bug treatment effect percentile is based on the reverse ranking of t-statistics for the interaction term *Post* × *Android app*, with *%Bug* as the dependent variable. We then calculate the total treatment rank for each VC based on the sum of the three treatment percentiles. Each dot in the graph represents one VC, with the dot at the top corresponding to GV, which ranks the highest overall in terms of treatment effect among all 128 VCs.

Table 1: Summary statistics

Statistic	N	Mean	SD	P25	P50	P75
Panel A: Android app metadata						
Total downloads	1436	21.719	200.534	0.012	0.094	1.218
Mean rating	1436	3.654	1.157	3.286	3.995	4.447
App age	1436	6.851	2.811	4.453	6.721	8.970
Panel B: Quarterly statistics for all sample apps						
Android apps:						
Review volume	39103	729.969	2868.851	1.000	9.000	120.000
Mean rating	30510	3.399	1.145	2.663	3.641	4.309
%Bug	30510	0.060	0.136	0.000	0.013	0.056
iOS apps:						
Review volume	39103	157.107	559.660	0.000	4.000	42.000
Mean rating	26884	3.226	1.223	2.318	3.333	4.268
%Bug	26884	0.081	0.162	0.000	0.019	0.086
Panel C: Quarterly statistics for GV apps						
Android apps:						
Review volume	747	2527.770	6256.816	11.500	138.000	842.500
Mean rating	709	3.663	0.856	3.167	3.852	4.309
%Bug	709	0.044	0.085	0.007	0.019	0.042
Update frequency	747	6.276	5.817	2.000	5.000	9.000
iOS apps:						
Review volume	747	660.537	1247.360	8.000	75.000	464.500
Mean rating	683	3.693	1.013	3.010	3.973	4.466
%Bug	683	0.046	0.102	0.000	0.022	0.050
Update frequency	747	6.111	4.494	3.000	5.000	9.000
Panel D: Yearly statistics						
Funding rounds	5887	0.281	0.521	0.000	0.000	0.000
Total funding	5887	14.768	50.413	0.000	0.000	0.000
Funding per round	5887	12.906	43.461	0.000	0.000	0.000
Log(review volume)	5887	4.247	2.896	1.792	3.951	6.349
ΔLog(review volume)	5887	0.268	0.952	-0.323	0.088	0.693
ΔMean rating	5027	-0.084	0.889	-0.440	-0.066	0.267
Δ%Bug	5027	0.007	0.115	-0.014	0.000	0.018

Panel A presents the metadata statistics for the Android apps included in the sample as of July 2023. *Total downloads* (in millions) is the cumulative number of downloads for each app. *Mean rating* is the average star rating provided by app users. *App age* is the app's age in years as of July 2023. Panel B presents the quarterly statistics for all the apps developed by VC-backed startups in our sample. Panel C reports the quarterly statistics for the 22 apps developed by GV-backed startups included in the DiD analysis in Section 4. *Review volume* is the total number of reviews posted by app users. *Mean rating* is the average star rating provided by app users. *%Bug* is the proportion of reviews that contain keywords related to app bugs. Panel D presents the yearly statistics for the sample Android apps used in the analysis in Section 5.1. *Funding rounds* is the number of funding rounds that app developers undergo within a calendar year. *Total funding* (in millions) is the total amount of equity financing raised by app developers within a calendar year. *Funding per round* (in millions) is the ratio of *Total funding* to *Funding rounds* for each calendar year. *Log(review volume)* is the natural logarithm of one plus the number of reviews. Δ*Log(review volume)* is the yearly difference in *Log(review volume)*. Δ*Mean rating* is the yearly difference in *Mean rating*. Δ*%Bug* is the yearly difference in *%Bug*. All variables are winsorized at the 1st and 99th percentiles.

Table 2: App visibility on Google Play: univariate comparison

	# Apps	Overall visibility	Within-category visibility	Cross-category visibility	# Visible categories
GV app	57	30.42	10.46	19.96	4.89
Other-VC app	287	6.85	3.00	3.85	1.18
GV app − Other-VC app		23.57***	7.45***	16.11***	3.71***
		(T = 4.05)	(T = 3.33)	(T = 3.6)	(T = 4.13)

This table presents the visibility of Android apps associated with various types of VCs. *GV app* refers to apps developed by startups invested by GV. *Other-VC app* refers to apps from startups invested by VCs that have never co-invested with GV. The app visibility metric, *Overall visibility*, is measured based on the frequency an app appears as a "similar app" within the network of 9,225 Android apps. We further divide *Overall visibility* into two types of visibility: *Within-category visibility* measures the number of times each app appears as a "similar app" on the homepages of other sample apps within the same genre; *Cross-category visibility* measures the number of times each app appears as a "similar app" on the homepages of other sample apps of different genres. *# Visible categories* is the unique number of genres among the apps that recommend this app as a "similar app". We conduct t-tests on the differences in visibility between GV apps and other-VC apps and present the t-statistics in parentheses. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Table 3: App visibility on Google Play: regression analysis

	Overall visibility	Within-category visibility	Cross-category visibility	# Visible categories
	(1)	(2)	(3)	(4)
GV	1.022***	0.590*	1.366***	0.886***
	(3.66)	(1.81)	(4.22)	(3.18)
App age	0.060	0.164***	-0.022	0.023
	(1.16)	(2.66)	(-0.42)	(0.52)
Log(# downloads)	0.221***	0.225***	0.233***	0.208***
	(5.43)	(5.14)	(4.63)	(4.87)
Mean rating	0.538**	0.506*	0.600**	0.577***
	(2.18)	(1.66)	(2.05)	(2.59)
App category FE	Y	Y	Y	Y
Observations	267	267	267	267
Pseudo R^2	0.460	0.472	0.491	0.404

This table presents the estimates of cross-sectional Poisson regressions of app visibility (see Model (1)). The dependent variable is the visibility of an Android app measured in four different ways: total number of recommendations as "similar app" (*Overall visibility*), number of recommendations as "similar app" from apps of the same genre (*Within-categoary visibility*), number of recommendations as "similar app" from apps of different genres (*Cross-categary visibility*), and the number of different genres where the app shows up as a "similar app" (*# Visible categories*). *GV* is a binary variable that equals one for apps developed by startups invested by GV. *App age* is the app's age in years as of July 2023. *Log(total downloads)* is the natural logarithm of the cumulative number of downloads for each app. *Mean rating* is the average app rating collected from the app metadata. We include the app category (i.e., genre) fixed effects in the regressions. We report t-statistics based on robust standard errors in parentheses. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Table 4: App visibility rank

Panel A: Absolute rank			
	Overall rank	Within-category rank	Cross-category rank
GV app	35.75	31.77	37.01
Other-VC app	42.61	36.86	45.59
GV apps − Other-VC app	-6.85	-5.08	-8.58
	(T = -1.38)	(T = -0.96)	(T = -1.66)
Panel B: Percentile rank			
	Overall percentile rank	Within-category percentile rank	Cross-category percentile rank
GV app	0.52	0.46	0.54
Other-VC app	0.56	0.51	0.58
GV apps − Other-VC app	-0.04	-0.05	-0.04
	(T = -1.23)	(T = -1.21)	(T = -1.02)

This table presents the visibility rank of Android apps associated with various types of VCs. The visibility rank is measured based on the position of each app on the list of "similar apps" suggestions. *GV app* refers to apps developed by startups invested by GV. *Other-VC app* refers to apps from startups invested by VCs that have never co-invested with GV. Panel A presents the absolute visibility ranks of apps. *Overall rank* is the average position of an app in the "similar app" suggestions by all sample apps. *Within-category rank* is the average position of an app in the "similar app" suggestions by sample apps of the same genre. *Cross-category rank* is the average position of an app in the "similar app" suggestions by sample apps of different genres. Panel B presents the reversed percentile visibility ranks of apps, with a lower value suggesting a higher rank. *Overall percentile rank* is the average percentile position of an app in the "similar app" suggestions by all sample apps. *Within-category rank* is the average percentile position of an app in the "similar app" suggestions by sample apps of the same genre. *Cross-category rank* is the average percentile position of an app in the "similar app" suggestions by sample apps of different genres. We conduct t-tests on the differences in visibility ranks between GV apps and other-VC apps and present the t-statistics in parentheses. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Table 5: Percentage of apps with at least 10% removal of negative reviews

	Android apps	iOS apps
GV app	13.16%	8.57%
Other-VC app	3.69%	5.91%
GV app − Other-VC app	9.47%**	2.66%
	(Z = 2.50)	(Z = 0.59)

This table shows the percentage of apps with at least 10% of their negative reviews removed between two data snapshots for GV-backed and other-VC-backed apps, across Android and iOS platforms. The data covers reviews posted from July 2022 to June 2023. For Android apps, the snapshots were collected in July 2023 and January 2024; for iOS apps, the snapshots were collected in September 2023 and September 2024. Negative reviews are defined as those with 1- or 2-star ratings. *GV app* refers to apps developed by startups backed by GV and without an exit status as of July 2023, ensuring GV's ownership during the data collection period. *Other-VC app* refers to apps developed by startups backed by VCs that have never co-invested with GV. We report z-statistics for the differences in proportions between the two groups in parentheses. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Table 6: Review removals between two snapshots of review data

	# Obs	% Change in negative review vol	% Change in neutral review vol	% Change in positive review vol	% Change in bug-related review vol
Panel A: Android apps from Google Play					
GV app	38	-5.21%	-1.91%	-1.28%	-4.71%
Other-VC app	244	-1.75%	-1.64%	-0.97%	-1.10%
GV app − Other-VC app		-3.46%**	-0.27%	-0.30%	-3.61%**
		(T = -2.13)	(T = -0.45)	(T = -0.82)	(T = -2.48)
Panel B: iOS apps from Apple's App Store					
GV app	35	-3.14%	-6.42%	-1.59%	-3.60%
Other-VC app	186	-1.99%	-0.96%	-1.43%	-0.98%
GV app − Other-VC app		-1.15%	-5.46%*	-0.16%	-2.62%
		(T = -1.22)	(T = -1.86)	(T = -0.27)	(T = -1.60)
Panel C: Android apps from Google Play with at least 20 reviews					
GV app	23	-4.98%	-3.16%	-2.11%	-7.78%
Other-VC app	106	-2.30%	-2.68%	-1.92%	-1.79%
GV app − Other-VC app		-2.69%**	-0.47%	-0.19%	-5.99%**
		(T = -2.73)	(T = -0.58)	(T = -0.35)	(T = -2.75)

This table presents the percentage changes in review volume across two data snapshots for GV-backed and other-VC-backed apps, grouped by platform (Google Play and Apple's App Store) and review type. The data covers reviews posted between July 2022 and June 2023. For Android apps (Panel A), the two snapshots were collected in July 2023 and January 2024; for iOS apps (Panel B), the two snapshots were collected in September 2023 and September 2024. Review types are categorized into negative (1–2 stars), neutral (3–4 stars), positive (5 stars), and bug-related reviews. The analysis includes only apps with non-zero reviews in both snapshots: 38 GV apps and 244 other-VC apps for Android, and 35 GV apps and 186 other-VC apps for iOS. *GV app* refers to those developed by startups invested by GV that have not achieved exit status as of July 2023, ensuring GV's ownership during the data collection period. *Other-VC app* refers to those developed by startups backed by VCs that have never co-invested with GV. In Panel C, we repeat the analysis in Panel A but restrict the sample to Android apps with more than 20 reviews in the first snapshot to focus on well-established apps. We report t-statistics for the differences in the review removal rate in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Content analysis of removed reviews

	Accuracy	Precision	Recall
Training set (other-VC apps)	0.65	0.75	0.46
Validation set (other-VC apps)	0.64	0.74	0.44
Testing set (GV apps)	0.54	0.60	0.24

This table presents the performance of the trained neural network model across different datasets. We construct a balanced dataset of 4,160 removed negative reviews and 4,160 randomly chosen retained negative reviews from the Android reviews of other-VC apps, covering the same period (July 2022 to June 2023). We use 80% of this dataset as a training set to train the model and the remaining 20% as a validation set for out-of-sample testing. During the training stage, we deploy the BERT model to process the review texts from the training set and use the processed outputs as inputs for a 4-layer neural network to test if the model could differentiate between removed and retained reviews based on review content. Then, we conduct separate out-of-sample tests on the validation set from other-VC apps and the testing set from GV apps. The testing set includes 678 negative reviews from GV apps, among which 339 are removed negative reviews and 339 are randomly chosen from the retained negative reviews.

Table 8: Changes in the app review volume after GV investment: Android versus iOS

	Log(review volume)		
	(1)	(2)	(3)
Android app	0.155	0.155	0.155
	(0.62)	(0.61)	(0.62)
Post	1.251***	0.867***	
	(3.18)	(2.86)	
Post × Android app	0.765***	0.765***	0.765***
	(3.01)	(2.95)	(3.01)
App pair FE	N	Y	N
Quarter FE	N	Y	N
App pair × Quarter FE	N	N	Y
Observations	1494	1494	1494
Adjusted R^2	0.080	0.835	0.918

This table presents the estimates of Model (3) using *Log(review volume)*, the natural logarithm of one plus the number of reviews, as the dependent variable. The Android and iOS versions of the same app constitute an app pair. The sample consists of 1,494 app-quarter observations from January 2010 to June 2023 for 22 app pairs developed by 17 startups that were backed by GV during that period. To ensure a sufficient pre-investment period, an app pair is included in the sample only if both its Android and iOS versions were launched at least two quarters before GV's investment. *Android app* is a binary variable that equals one for the Android version of an app pair, and zero for the iOS version. *Post* is a binary variable that equals one for observations after GV's investment. We include alternative combinations of app pair fixed effects, quarter fixed effects, and app pair × quarter fixed effects in the regressions. We report t-statistics based on standard errors clustered at the app pair level in parentheses. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Table 9: Changes in the average app rating after GV investment: Android versus iOS

	Mean rating		
	(1)	(2)	(3)
Android app	-0.349**	-0.320*	-0.336**
	(-2.21)	(-2.03)	(-2.30)
Post	-0.503***	-0.175	
	(-3.48)	(-1.28)	
Post $\times$ Android app	0.426**	0.424**	0.452***
	(2.36)	(2.41)	(2.88)
App pair FE	N	Y	N
Quarter FE	N	Y	N
App pair $\times$ Quarter FE	N	N	Y
Observations	1392	1392	1328
Adjusted R^2	0.025	0.363	0.441

This table presents the estimates of Model (3) using *Mean rating*, the average app rating, as the dependent variable. The Android and iOS versions of the same app constitute an app pair. The sample consists of 1,392 app-quarter observations from January 2010 to June 2023 for 22 app pairs developed by 17 startups that were backed by GV during that period and have non-zero number of reviews. To ensure a sufficient pre-investment period, an app pair is included in the sample only if both its Android and iOS versions were launched at least two quarters before GV's investment. *Android app* is a binary variable that equals one for the Android version of an app pair, and zero for the iOS version. *Post* is a binary variable that equals one for observations after GV's investment. We include alternative combinations of app pair fixed effects, quarter fixed effects, and app pair $\times$ quarter fixed effects in the regressions. We report t-statistics based on standard errors clustered at the app pair level in parentheses. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Table 10: Changes in the proportion of bug-related reviews after GV investment: Android VS iOS

	%Bug		
	(1)	(2)	(3)
Android app	0.022	0.020	0.024*
	(1.71)	(1.71)	(2.00)
Post	0.005	0.015	
	(0.41)	(1.11)	
Post × Android app	-0.033**	-0.032**	-0.034**
	(-2.48)	(-2.60)	(-2.62)
App pair FE	N	Y	N
Quarter FE	N	Y	N
App pair × Quarter FE	N	N	Y
Observations	1392	1392	1328
Adjusted R^2	0.007	0.095	0.182

This table presents the estimates of Model (3) using *%Bug*, the proportion of reviews that contain keywords related to app bugs, as the dependent variable. The Android and iOS versions of the same app constitute an app pair. The sample consists of 1,392 app-quarter observations from January 2010 to June 2023 for 22 app pairs developed by 17 startups that were backed by GV during that period and have non-zero number of reviews. To ensure a sufficient pre-investment period, an app pair is included in the sample only if both its Android and iOS versions were launched at least two quarters before GV's investment. *Android app* is a binary variable that equals one for the Android version of an app pair, and zero for the iOS version. *Post* is a binary variable that equals one for observations after GV's investment. We include alternative combinations of app pair fixed effects, quarter fixed effects, and app pair × quarter fixed effects in the regressions. We report t-statistics based on standard errors clustered at the app pair level in parentheses. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Table 11: GV treatment effects and app updates

	Log(review volume) (1)	Mean rating (2)	%Bug (3)
Android app	-0.061	-0.430	0.032*
	(-0.25)	(-1.44)	(1.99)
Lag update freq	0.014	-0.013	-0.000
	(0.37)	(-0.33)	(-0.17)
Post × Android app	0.739***	0.457	-0.042**
	(3.82)	(1.50)	(-2.33)
Android app × Lag update freq	0.052	0.021	-0.002
	(1.51)	(0.49)	(-0.53)
Post × Lag update freq	0.063	0.040	-0.001
	(1.51)	(1.03)	(-0.59)
Post × Android app × Lag update freq	-0.018	-0.010	0.002
	(-0.46)	(-0.22)	(0.59)
App pair × Quarter FE	Y	Y	Y
Observations	1494	1328	1328
Adjusted R^2	0.928	0.451	0.182

This table presents the estimates of Model (4) using three difference measures of app performance as the dependent variable: the natural logarithm of one plus the number of reviews (*Log(review volume)*), the average app rating (*Mean rating*), and the proportion of reviews that contain keywords related to app bugs (*%Bug*). The Android and iOS versions of the same app constitute an app pair. The sample consists of 1,494 app-quarter observations, including 1,328 observations with non-zero reviews, from January 2010 to June 2023 for 22 app pairs developed by 17 startups that were backed by GV during that period. To ensure a sufficient pre-investment period, an app pair is included in the sample only if both its Android and iOS versions were launched at least two quarters before GV's investment. *Android app* is a binary variable that equals one for the Android version of an app, and zero for the iOS version. *Post* is a binary variable that equals one for observations after GV's investment. *Lag update freq* is the frequency of updates for each app version in the previous quarter. We include alternative combinations of app pair fixed effects, quarter fixed effects, and app pair × quarter fixed effects in the regressions. We report t-statistics based on standard errors clustered at the app pair level in parentheses. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Table 12: Financing outcomes across VC types

	# startups	Average funding rounds	Average total funding	Average funding per round
GV	42	5.95	639.46	72.86
Other VC	197	2.68	30.29	11.16
GV − Other VC		3.28***	609.16**	61.70***
		(T = 5.78)	(T = 2.58)	(T = 3.54)

This table presents the financing outcomes for startups affiliated with GV and other VCs that have never engaged in co-investments with GV during the sample period. *Funding rounds* is the cumulative number of funding rounds secured by the startups during the sample period. *Total funding* (in millions) is the cumulative amount of financing raised by the startups throughout the sample period. *Funding per round* (in millions) is the average amount of financing the startups raise per funding round. We report t-statistics for the differences in the financing outcomes between the two groups in parentheses. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Table 13: App performance and financing outcomes

	One-year-ahead $I_{Funding}$	One-year-ahead Log(Total funding)	One-year-ahead Log(review volume)
	(1)	(2)	(3)
ΔLog(review volume)	0.018**	0.090***	0.170***
	(2.39)	(3.43)	(8.35)
ΔMean rating	0.013*	0.042*	0.044***
	(1.65)	(1.68)	(2.77)
Δ%Bug	0.045	0.162	-0.233**
	(0.81)	(0.91)	(-1.97)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	4947	4947	4032
Adjusted R^2	0.174	0.214	0.910

This table reports the estimates of startup firm-year panel regressions. The sample includes 1,024 startups with VC financing and at least one Android app. In columns 1 and 2, the dependent variables are measures of financing outcomes, including a binary variable that equals one if the sample startup obtained financing in the subsequent year (*One-year-ahead* $I_{Funding}$) and the natural logarithm of one plus the total amount of financing raised by the startup in the subsequent year (*One-year-ahead Log(Total funding)*). In column 3, the dependent variable is the natural logarithm of one plus the total review volume in the subsequent year (*One-year-ahead Log(review volume)*). Δ*Log(review volume)* is the yearly difference in the natural logarithm of one plus the yearly review volume. Similarly, Δ*Mean rating* is the yearly difference in *Mean rating* calculated from the review ratings. Δ*%Bug* is the yearly difference in *%Bug*. For each startup, we measure the app-level metrics in the regressions based on its most downloaded app. We include firm and year fixed effects in the regressions. We report t-statistics based on standard errors with startup clustering in parentheses. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Table 14: Startup exit status across VC types

	# startups	# exits	# IPO	% IPO	% Exit
GV	42	11	5	11.90%	26.19%
Other VC	197	42	11	5.58%	21.32%
GV − Other VC				6.32%	4.87%
				(Z = 1.49)	(Z = 0.69)

This table presents the rate of successful exit for startups backed by GV and other VCs that have no syndication connection with GV. *% Exit* indicates the percentage of startups that have achieved a successful exit by the end of the sample period. Successful exit events include mergers, IPOs, secondary sales, direct public offerings, write-offs, buybacks, and reverse takeovers. *% IPO* is the percentage of startups that have successfully completed an initial public offering by the end of the sample period. We report z-statistics for the differences in proportions between the two groups in parentheses. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively.

Table 15: App visibility and the review removal rate for Android apps backed by connected VCs

Panel A: App visibility

	# Apps	Overall visibility	Within-category visibility	Cross-category visibility	# Visible categories
Connected-VC app	1092	15.08	7.50	7.58	2.20
Other-VC app	287	6.85	3.00	3.85	1.18
Connected-VC app − Other-VC app		8.23***	4.50***	3.73***	1.02***
		(T = 5.33)	(T = 5.49)	(T = 3.74)	(T = 4.33)

Panel B: Changes in review volume

	# Apps	% Change in negative review vol	% Change in neutral review vol	% Change in positive review vol	% Change in bug-related review vol
Connected-VC app	958	-2.69%	-2.47%	-1.82%	-2.06%
Other-VC app	244	-1.75%	-1.64%	-0.97%	-1.10%
Connected-VC − Other-VC app		-0.95%***	-0.83%*	-0.85%***	-0.96%***
		(T = -2.78)	(T = -1.93)	(T = -3.11)	(T = -2.85)

This table presents the differences in app visibility and the review removal rate between apps backed by connected VCs and those backed by other VCs. *Connected-VC app* refers to apps developed by startups invested by VCs that are connected with GV through syndication. *Other-VC app* refers to the apps developed by startups invested by VCs that have never co-invested with GV. Panel A of Table 15 presents the difference in app visibility between connected-VC apps and other-VC apps, following the methodology in Table 2. The visibility of an Android app measured in four ways: total number of appearances as "similar app" (*Overall visibility*), number of appearances as "similar app" for apps of the same genre (*Within-categoary visibility*), number of appearances as "similar app" for apps of different genres (*Cross-categary visibility*), and the number of different genres where the app shows up as a "similar app" (*# Visible categories*). We conduct t-tests on the differences in visibility between GV apps and other-VC apps and present the t-statistics in parentheses. *, ** and *** indicate significance better than 10%, 5%, and 1% respectively. Panel B of Table 15 presents the difference in the review removal rate between connected-VC apps and other-VC apps from Google Play, following the methodology in Panel A of Table 6. We separately count four types of reviews: negative reviews (1 and 2-star ratings), neutral reviews (3 and 4-star ratings), and positive reviews (5-star ratings). We report t-statistics for the differences in the review removal rate in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.