Performance Indicators of the Digital Age: Mobile Apps, Firm Disclosure, and Stock Returns

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Abstract

Mobile apps, iOS or Android apps downloadable onto smartphones and tablets, are becoming an important part of the global economy. Mobile apps facilitate earnings generation by being the primary (or an alternative) platform of product delivery, via in-app purchases or advertisements. and better customer engagement by leveraging insights derived from real-time user data collected by apps. We demonstrate that mobile app download is a leading performance indicator as mobile app downloads significantly predict subsequent quarter's earnings. Notably app downloads predict earnings for all firms, not just firms that rely primarily on apps to generate revenue (i.e., firms with apps with in-app purchase options and in-app ad placements), but also brick-and-mortar firms with established brands that adopt mobile apps as an alternative way to deliver products. However, the investment community does not fully comprehend the value of mobile apps: we find that mobile app downloads significantly predict analyst forecast errors and future returns. A long-short strategy on abnormal downloads delivers an EW (VW) annualized return of 12% (9%). Analysts' and investors' misunderstanding appears to be concentrated in the subsample of firms where they cannot directly observe apps' revenue generating capabilities, i.e., firms whose apps do not have in-app purchase options or ad placements. Importantly, firm disclosure on mobile apps in regulatory filings mitigates the predictability of analyst forecast errors and returns. Our study advances our understanding of new performance indicators of the digital economy and the role of disclosure in facilitating such understanding for the investment community.

Keywords: Mobile apps, mobile app download, leading performance indicator, firm disclosure, analysts forecast error, SUE, investors, hedge portfolio returns, digital economy

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1. Introduction

The exponential growth of computing power and the innovation in digital technologies have fundamentally transformed the global economy. One such innovative digital technology is mobile apps (or apps in short), iOS or Android apps that can be downloaded onto smartphones and smart tablets. Mobile apps can generate significant economic benefits: for example, Apple's app store ecosystem facilitated more than $1.1 trillion in billings and sales worldwide in 2022.[1] Prominent practitioners' journals such as the *Wall Street Journal* and *New York Times* have documented the increasing adoption of mobile apps across different industries, and a recent *Forbes* article reports that digital banking has become the most common way consumers bank today: by 2021, more than 43% of consumers use mobile banking, far surpassing other forms of banking such as online banking (22%) and using ATMs (16%).[2]

Mobile apps facilitate the generation of revenue either by being the primary platform (e.g., Uber) or an alternative platform of product delivery (e.g., grocery store apps such as Kroger), and/or through recurring subscription fees (e.g., dating apps from Bumble Inc.), in-app purchase options and/or in-app advertisement placement (e.g., Twitter, game apps from AppLovin Corp, TripAdvisor, Facebook). All apps that collect customer data can further enhance revenue generation through better customer engagement and retention by leveraging insights derived from real-time user data (Stocchi et al., 2022). Major industry news outlets such as Tech.Crunch.com actively track mobile app user download data as a leading indicator of growth in the tech and app

[1] "The continued growth and resilience of Apple's app store ecosystem," Analysis Group, 2023.
[2] "Smart Phone Apps Fuel Business," The *Wall Street Journal*, August 20, 2009; "How Restaurants are Using Big Data as a Competitive Tool," The *Wall Street Journal*, October 2, 2018; "Mobile Apps are a Must for Most Brands, as Long as Users Like Them," *The New York Times,* June 17, 2018; "WhatsApp's Business User Base Grew Tenfold from 2019," *The Wall Street Journal*, July 9, 2020; https://www.forbes.com/advisor/banking/banking-trends-and-statistics/.

industry. Firms develop algorithms to track user engagement and discuss user growth in their earnings calls (e.g., Pinterest, TripAdvisor, Starbucks Coffee), and some firms also disclose app-related information in their regulatory filings such as 10-Ks, 10-Qs, and 8-Ks. For example, Bumble and AppLovin discuss app user count as an important performance metric, explicitly acknowledging obtaining new users, and user retention and engagement as important risk factors, and tabulate detailed revenue per app user in their filings such as 10-Ks.

Despite the focus of industry practitioners and firms on the value of mobile apps, accounting research appears to lag behind in understanding the role of mobile apps in facilitating revenue generation for the digital age. We attempt to bridge this gap by addressing three related research questions: First, can mobile app information predict future performance? Second, do analysts and investors fully incorporate information about mobile apps in their research outputs and investment decisions? Third, does firm disclosure of mobile app information help analysts and investors better understand the valuation implications of mobile apps?

To address our research questions, we obtain user download data from Sensor Tower, a leading global mobile app data provider. Sensor Tower offers data on millions of mobile apps from more than 100 countries. In this paper, we use app download data for apps owned by U.S. public companies from 2012 to 2021.[3] Our sample consists of 835 unique public U.S. companies (approximately 9% of the Compustat population during our sampling period), and spans a wide range of industries from personal and business services to retail, transportation, banking, healthcare, and other industries. Although our sample of public firms constitutes a very small portion of all firms globally (both private and public) with mobile apps, the total number of app downloads of our sample firms is about 20% of the total worldwide downloads in recent years,

[3] App downloads are available for all covered apps in the database. An alternative measure of time-varying app activity in Sensor Tower is the number of active users. However, Sensor Tower estimates this measure with strong assumptions and high requirements on data availability, and thus only about 10% of the apps have the information.

according to data from Sensor Tower, suggesting that our sample firms are important in the global mobile economy.

We first establish mobile app download as a leading performance indicator. App downloads are widely used in the app industry to measure user growth.[4] We demonstrate that quarterly app downloads significantly and positively predict subsequent quarter's earnings. For an average-size firm in our sample, a 10% increase in downloads predicts an increase of $10 million in earnings per quarter. This predictive power is robust to the inclusion of firm size, current earnings, book-to-market ratio, R&D expenditure, capital investment, SG&A expenditure, and intangible assets and its various components, such as software development costs and goodwill, in our regressions.

It is possible that mobile apps are more important to firms such as Bumble and AppLovin that rely heavily on apps to deliver their products, but less important for traditional brick-and-mortar companies such as McDonald's or Walmart. It is even possible that mobile app information cannot predict future performance for the latter group of firms at all. We construct an indicator variable coded as one for firms with apps that contain either an in-app purchase option or in-app ad placements, and zero otherwise. This in-app revenue indicator variable captures apps' direct revenue-generating features that are observable to users. We obtain data on these two app revenue-generating features from Sensor Tower. We classify 167 firms as in-app-revenue firms, including firms such as NetEase, dating app firm Meet Group, Paypal, Twitter, and Pandora. We re-estimate the earnings prediction model for two the subsamples split on the indicator. Noteworthy is the finding that app downloads significantly predict future earnings in both subsamples, suggesting that app download is a leading performance indicator for both firms that rely primarily on mobile apps and firms that adopt apps as an alternative platform to deliver products. Consistent with our expectations, the point estimates on app downloads are larger for in-app-revenue companies.

[4] https://buildfire.com/mobile-app-value.

To address our second research question of whether analysts and investors recognize the importance of app download as a leading performance indicator, we first examine whether analysts incorporate app-related information in their earnings forecasts. If analysts adequately incorporate the value of mobile apps into their earnings forecasts, then lagged downloads should not predict analysts' future earnings forecast errors. Following Lee, Sun, Wang, and Zhang (2019), we regress standardized unexpected earnings (SUEs), constructed as the standardized difference between actual earnings and analyst consensus earnings forecasts, on lagged app downloads and the last four quarters' SUEs, and additionally controlling for R&D expenditure, capital investments, and SG&A expenditure. We find that lagged app downloads have significant predictive power for future SUEs, consistent with analysts not fully incorporating the information related to mobile apps in their earnings forecasts.

Given that analysts are sophisticated information intermediaries, the above finding begs the question of whether analysts completely fail to understand the importance of mobile app data for all app firms. Some analysts do include discussions related to mobile app information, such as app downloads and revenue per user, etc., in their research reports.[5] Thus, it is likely that analysts are better at understanding the importance of apps for some firms, as long as they have access to information to assess apps' earnings generating capabilities. We split our sample based on our in-app-revenue indicator, and re-estimate the SUE prediction regressions for both subsamples. We find that mobile app downloads' predictive power for future SUEs primarily resides in non-in-app-revenue firms. Coupled with our finding above that app downloads can predict performance for all firms, the subsample results on SUE predictability suggest that analysts are able to incorporate the value of apps in their earnings forecasts only when they have information about apps' revenue generating abilities, but not when apps' revenue generating ability is not directly observable from

[5] https://www.reuters.com/technology/bumble-slumps-ceo-signals-need-app-revamp-after-poor-earnings-2024-02-28/.

app features.

We apply a similar analysis to examine whether investors understand the valuation implication of mobile apps. If investors fully incorporate the valuation implication of mobile apps in their investment decisions, app downloads should not be able to predict future returns. We resort to a portfolio sorting approach to examine the ability of lagged abnormal app downloads (downloads subtracted by the average downloads of the past ten quarters) to predict future returns. We use abnormal downloads to remove firm-specific effects regarding companies' mobile app adoption, which is similar to including firm-fixed effects, while ensuring that all information is available at the time of portfolio formation. A long-short strategy in the highest and lowest deciles of abnormal app downloads produces an equally weighted (value-weighted) hedge portfolio returns of 98 (74) basis point per month, suggesting that investors are leaving substantial money on the table. The portfolio's alphas remain significantly positive in Fama-MacBeth regressions of various asset pricing models, including CAPM, Fama-French three-factor, Carhart four-factor, Fama-French five-factor, and five-factor plus the momentum factor models.

To further ensure that app downloads' predictive ability for future returns is not because of unobservable risk factors, we follow a long line of literature and examine whether the relation between abnormal downloads and returns is stronger around subsequent quarter's earnings announcements (Bernard and Thomas, 1989; Lee et al. 2020). If investors' expectations are biased due to a lack of understanding of the value of mobile apps, earnings announcements should lead investors to update their beliefs and a price correction, resulting in a stronger price reaction around earnings announcements, whereas a risk explanation would lead to returns that accrue evenly over subsequent periods instead of spiking around earnings announcements (Engelberg, Mclean, and Pontiff 2018). Following this prior literature, we regress daily returns around the earnings announcement windows on beginning of the quarter abnormal downloads. The coefficient on lagged abnormal downloads is

0.281 using a five-day earnings announcement window, whereas a baseline regression of daily stock returns on lagged abnormal downloads yields a coefficient of 0.020. This spike in reaction around the earnings announcement window is hard to square with a risk explanation.

We conduct a similar cross-sectional analysis by splitting our sample based on the in-app-revenue indicator. Similar to our cross-sectional results on SUE predictability, the predictive ability of abnormal downloads for future returns resides primarily in firms with apps that do not have in-app purchase options or in-app ad placements, but not in firms with apps that contain in-app revenue generating features. This suggests that the availability of information helps investors recognize the importance of apps for these firms, and that when such information is not readily available, investors fail to appreciate the valuation implications of mobile apps.

The concentration of app downloads' predictive ability for SUE and future returns in the subsample of firms for which apps' revenue generating ability is not directly observable raises the question of whether firm disclosure, the type of information that imposes the lowest information acquisition costs, can help analysts and investors improve their understanding of the valuation implications of mobile apps.

Toward this end, we construct a firm disclosure measure using the average mentions of mobile app-related information across the top three regulatory filings – firms' 10-K, 10-Q, and 8-K reports filed with the U.S. Securities and Exchange Commission (SEC). As this measure only counts related words and phrases, it likely captures a lower bound of app-related disclosure by firms that provide such disclosure, as some firms (such as Bumble and AppLovin) also provide detailed quantitative information, usually in tables and graphs, on app-related statistics, such as the revenue generated per user per time period. However, we note that this should not affect our inference as long as firms' total disclosure about apps is positively related to our word count measure, as we rely on this measure to identify cross-sectional differences only.

We expect that firms to whom apps are more important would provide more app-related disclosure. We regress our mobile app disclosure measure on our in-app revenue indicator variable which captures the importance of apps to firms, as well variables capturing firm size, market to book, R&D expenditure, capital investment, SG&A expenses, as well as measures for proprietary cost concerns and industry competition. The coefficients on the in-app revenue indicator variable are significantly positive, consistent with our expectation.

We repeat the SUE predictability and future return predictability analysis by splitting our sample based on the sample median of our firm disclosure measure. Consistent with firm disclosure helping analysts and investors better understand the valuation implication of mobile apps, we find that app download's predictive power for future SUEs disappears for the subsample of firms with above sample-median disclosure. The predictability of abnormal app downloads for future returns also disappears for the subsample of firms with greater disclosure. Taken together, this set of results suggests that firm disclosure allows the investment community to better understand the importance of mobile apps to firm performance.

The research on mobile apps as an important contributor to the digital economy is scarce. To the best of our knowledge, we are aware of only two other papers: Wu (2023) and Ferracuti, Koo, Lee, and Stubben (2024). Wu (2023) derives a mobile app-value measure from the market reaction to app release, and shows that this app value can predict lower firm risk, higher future growth, and increased market power. Ferracuti et al. (2024) find that after app adoption, management guidance is more accurate, and firms constrain their underinvestment in capital assets and overinvestment in inventory. Our paper complements these two papers in bringing a greater awareness to the importance of mobile apps to firms and the investing public. We also advance this research by further delving into the role of firm disclosure in facilitating our collective understanding of mobile apps as an important indicator of future performance.

Our research extends early research on the value relevance of non-financial information for high-technology, high-growth firms (Amir and Lev 1998; Truman, Wong, and Zhang 2000; Rajgopal, Venkatatchalam, and Kotha 2003). Our study also complements research on non-financial performance indicators of the traditional, brick-and-mortar economy (e.g., Givoly, Li, Lourie, and Nekrasov 2019), and the research using alternative data to examine manager behavior (Dichev and Qian, 2018; Chiu, Teoh, Zhang, and Huang, 2023; Zhu 2019; Blankspoor, Hendricks, Piotroski, and Synn 2022). We note that mobile apps are different from traditional performance indicators (e.g., passenger load factors for airlines), which typically only reflect current performance but cannot generate or facilitate the generation of future revenue. Mobile app data is also different from alternative data such as satellite images, as mobile app usage data is internal to the firm, not externally generated by other enterprises. Our research highlights that mobile app usage is a new and unexplored leading performance indicator for firms owning apps.

Our finding that firm disclosure helps analysts and investors should provide useful food for thoughts for the SEC in its deliberation of disclosure standards (Leuz and Wysocki 2016). Mary Jo White, the former chair of the SEC, among others, has noted that the SEC's disclosure mandate is constantly expanding, focusing not only on financial performance, but a host of other issues.[6] For example, the SEC has recently required new disclosures on human capital, mine safety, conflict minerals, compliance with government regulations, and various pay to performance measures, and is currently deliberating climate risk disclosure rules. At the same time, we note that there are relatively few recent disclosure mandates focusing on value-relevant factors that can forecast performance, especially those for the digital economy. As the digital economy is increasingly contributing more value to the U.S. GDP, disclosure of the value-relevant factors can better facilitate resource allocation of the economy.[7]

[6] https://www.sec.gov/news/speech/spch100113mjw

[7] For example, according to the U.S. Bureau of Economic Analysis, in 2022, digital economy real value added grew by

2. Background and Related Literature

2.1 Mobile Apps

Mobile apps, iOS and Android apps that can be downloaded onto smart phones and smart tablets, have upended commerce by transforming the way consumers access products and services and by offering businesses real-time data driven insights. According to Kurve.co.uk, a London-based marketing agency for business-to-business consumer tech companies, from 2019 to 2022 daily app downloads globally exceed 255 million, and in 2022 consumers spend nearly 110 billion hours on shopping apps and expend $129 billion on in app purchases alone. Mobile apps are increasingly being adopted across different industries. Prominent practitioners' publications such as the *Wall Street Journal*, the *New York Times*, and *Forbes* have noted such adoption in consumer-facing industries such as restaurants, and in less obvious industries such as healthcare and banking.[8] The *Wall Street Journal* also notes that big companies in the Fortune 100 are playing catch-up in investing in mobile apps.[9]

Mobile apps offer the convenience of consumption on the go: users can access information and services, consume digital contents, browse products, read reviews, and make purchases directly through apps. This new way of delivering products and services greatly reduces the traditional friction in the purchasing process. For example, consumers can access digital content such as movies via mobile apps while traveling in the air, order groceries using mobile apps and have them delivered home without ever setting foot in the actual store, which saves not only cost of gas but also the time to drive in traffic and find parking. Some app firms such as Uber and Match Group Inc. (which owns Tinder, OkCupid, and other dating apps) rely predominantly on mobile apps to generate revenue. Mobile apps can also generate revenue directly through continuing

6.3% whereas the total U.S. real GDP growth is 1.9%.

[8] See Footnote 1.

[9] https://deloitte.wsj.com/cio/fortune-100-playing-catch-up-with-mobile-01671218440

subscription fees to access content (e.g. fitness apps such as Peloton), in-app purchase options (e.g. most game apps, language-learning app such as Duolingo, digital music streaming app Spotify), and in-app ad placements (e.g., Duolingo, Spotify, Facebook).

Many mobile apps collect valuable real-time data on user behavior, locations, preferences, and interactions. This data enables businesses to optimize marketing strategies and offer improved products or services in real time, lending to better customer engagement and greater retention (e.g., Starbucks Coffee, and many consumer facing apps). Starbucks Coffee's Q2 2017 and Q3 2019 earnings calls both attribute "personalized customer experience" as the "largest driver of increased consumer spending." Firms such as Bumble and AppLovin also prominently discuss attracting new app users, mobile app user retention and engagement as important risk factors in Item 1A of their 10-Ks. Many mobile apps, including that of Starbucks' Coffee, also contain gamification components and/or loyalty programs to incentivize user engagement. In sum, mobile apps provide valuable data-driven insights for businesses to make timely decisions to enhance their products and services, which further accelerates revenue generation. Consistent with this, Wu (2023) shows that a market-based app-value measure is associated with a significant reduction in firm-specific risk, particularly when apps collect user data.

2.2 Related Literature

Though industry practitioners and financial journalists recognize the importance of mobile apps, and firms themselves have also begun to include discussions of mobile apps in their regulatory filings, the literature on firms' use of mobile apps is thin. We are aware of only two other studies, Wu (2023) and Ferracuti et al. (2024). Wu (2023) constructs a market-based mobile app value measure, and shows that this measure of app value is negatively related to firm risk, and positively associated with future growth and increased market power. In addition, Wu (2023) shows that apps that collect data are twice as valuable as those that do not, and that firms with apps that collect data experience a larger reduction in idiosyncratic risks. Ferracuti et al. (2024) examine whether data collected via mobile apps aids firms' operating and investing decisions. They find that after app adoption, management earnings and revenue guidance is more accurate, and firms exhibit less underinvestment in capital assets and less overinvestment in inventory. We focus on a different aspect of the value of mobile apps: as a leading performance indicator for app firms, and the relation between app disclosure in firms' regulatory filings and investor valuation.

Our paper is related to an early literature on the value-relevance of non-financial information in fast-changing technology industries. This literature finds that for high-tech firms, non-financial information such as subscriber ratios for the wireless industry and web traffic for internet firms have greater association with stock prices than traditional accounting summary measures such as earnings and book value (Amir and Lev 1996; Truman et al., 2000; Rajgopal et al., 2003). These precedent studies by necessity usually focus on one specific industry. In contrast, the wide-spread adoption of mobile apps across different industries allows us to examine a broader set of the U.S. economy. We also note that after the early 2000s, studies investigating the extent to which financial statements reflect performance indicators of high-tech firms have tapered off. This lack of research further exacerbates the lack of our collective understanding of the new performance indicators of the digital economy.

Our research complements research on non-financial performance indicators of the traditional, brick-and-mortar economy (Givoly et al. 2019), which show that indicators such as passenger load factors for airlines have incremental information content for stock prices over earnings. We note that mobile apps are different from these traditional performance indicators, which typically only reflect current performance but cannot facilitate the generation of future revenue. As discussed above, mobile apps can generate revenue by being the primary (an alternative) product delivery platform, via in-app purchase options and ad placements, as well as via improved customer engagement and retention using real-time data collected. The same cannot be said of passenger load factors for airlines.

Our paper is also related to, but distinctly different from, a broader literature documenting the usefulness of external data to forecast revenue and detect earnings management. For example, Dichev and Qian (2018) use NielsenIQ Scanner data from U.S. retail chains to construct a measure of aggregated consumer purchases at the manufacturer/quarter level, and find that this measure can predict manufacturers' GAAP revenue. Chiu et al. (2023) show that Google product searches can be used together with reported sales to detect revenue manipulation. Other studies rely on alternative data such as real-time credit card purchases and satellite images to examine the interaction between these data and managerial behavior (Zhu, 2019; Blankspoor et al. 2022). The focus of our paper, mobile app data, is different from the data examined in this alternative-data literature because data on mobile apps are internal to the firm and immediately available to managers for real-time decision making. External data sources can provide useful information to the investing community, but cannot generate or facilitate the generation of future revenue or earnings as mobile apps can.

3. Data and Empirical Results

3.1 Data and Sample

Our primary data on mobile applications is from Sensor Tower, a leading provider of global mobile applications data and key metrics in the mobile industry. The Sensor Tower database contains a comprehensive collection of information on millions of mobile apps across more than 100 countries. In this paper, we use mobile app download data for apps owned by publicly listed companies in the United States from 2012 to 2021. Sensor Tower provides stock tickers for the parent companies of apps if these companies are publicly listed on major stock exchanges. We download all apps whose parent companies are publicly listed in the U.S. using the linking table from Sensor Tower. Because one stock ticker can be used by various companies at different times, and a publisher of an app might be a subsidiary of a publicly listed firm, we manually verify the matching of apps to firm names for each of the 835 firms in our sample.

For a given app in our sample, we use its download data in all available countries, in both the Apple App Store (iOS) and the Google Play Store (Android). The iOS app data is available from 2012, the starting year of the Sensor Tower data coverage, to the end of 2021, the time when the data was obtained. The Android data is available from 2014. For our main analyses, we use all available data including both iOS and Android downloads. In untabulated robustness analyses, we show that the results are qualitatively similar using only the iOS data that is available for a longer period.

We capture app user growth by using the app download data of each app. Sensor Tower combines actual data provided by their publishers and developer partners, and app rankings and metadata information from the App Store to estimate each app's daily downloads in each country. Downloads are recorded at the account level, and importantly, re-downloads by the same account (even across devices) are not counted in this measure. Thus, app downloads capture new downloads, which is essentially a changes measure. We also collect information on features of each app from Sensor Tower, including whether the app has in-app purchase options and whether the app has in-app advertisements in each period.[10]

We obtain firms' quarterly financial data from Compustat, stock price data from CRSP, and analyst forecast data from IBES. Because firm financial information is available at the quarter level, we aggregate app downloads at the quarter level across all apps owned by a given firm, and merge the download data with firm financial information.

Figure 1 presents graphical evidence on the increasing trend of app downloads worldwide

[10] We only have ad data for iOS apps.

(Panel A) and in our sample (Panel B) over our sampling period of 2012-2021. Globally, annual mobile app downloads increase from around 13.8 billion in 2012 to 142.7 billion in 2021, a greater than ten-fold increase. In our U.S. app firm sample the annual downloads increase over fivefold from around 4.6 billion in 2012 to over 23.3 billion in 2021.

We present descriptive statistics on app downloads and key variables in Table 1. In Panel A of Table 1 we compare our sample with the Compustat sample from major stock exchanges during the same time period, classified by Fama-French five industries. Our sample of 835 unique U.S. public companies accounts for around 9% of the 9,265 Compustat firms during our sampling period. Not surprisingly, the high-tech industry has the biggest ownership of mobile apps, accounting for 34% of the sample firms. The next big app-ownership industry is the consumer industry, including firms in consumer durables, nondurables, wholesale, retail, and some services, which accounts for 25% of the firms owning mobile apps.

In Panel B of Table 1 we present descriptive statistics on key variables used in our tests. Appendix A presents detailed definition of all our variables. All non-return variables are winsorized at the 0.5% and 99.5% levels to mitigate the impact of outliers. The raw number of quarterly app downloads (*DL*) is highly skewed, with a mean of 4,746 thousand and a median of 70.66 thousand. The firm disclosure measure *MobDis* is also highly right skewed with a mean word count of 18.5 per filing and a median word count of 2.3 per filing. The in-app revenue indicator variable $1_{inapp>0/ad>0}$ shows that 20% of our sample observations are firms with apps that have in-app revenue generating capabilities. We scale all variables by total assets (except for total assets and indicator variables), and we take log transformations of the scaled download measures as our main test variables (log (*DL/AT*) and log $(DL/AT)^{ab}$). We take the log transformation of the firm disclosure measure (log (*MobDis+1*)) without scaling by total assets as this is already a scaled measure (app-related word count averaged across three top regulatory filings).

Panel C of Table 1 presents the correlation matrix for the main test variables. Bolded correlation coefficients are statistically significant. Not surprisingly, all the app related measures, app downloads, the in-app revenue indicator, and the firm disclosure measure are all positively correlated with one another.

3.2 Are Mobile App Downloads a Leading Performance Indicator?

To establish mobile app downloads as a leading performance indicator, we regress quarter *q* earnings on quarter *q-1* log (*DL/AT*), and we control for quarter *q-1* net income, firm size, book to market ratio, R&D expenditures, capital investment, and SG&A expenses in quarter *q-1*. All variables in the regression (except for log total assets) are scaled by total assets.

The results are summarized in Table 2. Panel A of Table 2 presents the baseline results. Controlling for firm size (Column 1) and current earnings (Column 2), mobile app downloads (log (*DL/AT*)) positively and significantly predicts next quarter's earnings at the 1% level. In terms of economic magnitudes, for an average-size firm in our sample, a 10% increase in downloads is associated with an increase of $10 million (2.7% of sample mean) of earnings per quarter. The point estimate on mobile app downloads after including all the other control variables is 0.16, and remains significant at the 5% level.

Panel B of Table 2 further examines if existing balance sheet intangible asset accounts subsume the predictive ability of mobile app downloads for future earnings. The balance sheet accounts we consider are total intangible assets (*INTAN/AT*) and their components such as capitalized software development costs (*SFT/AT*), goodwill (*GW/AT*), and other intangible assets (*INTANO/AT*). Additionally, we also test whether the total Q measure (Q^{tot})from Peters and Taylor (2017) includes information from both R&D and capital investments subsumes the explanatory power of mobile app downloads for future revenue and earnings. After including these intangible asset accounts into our regressions, the point estimates of mobile app downloads remain positive and statistically significant, and the coefficients of 0.15 and 0.16 are similar to those obtained from Panel A.

We next examine if the inference that mobile app download is a leading performance indicator holds across firms that rely heavily on apps to generate revenue and more traditional firms that adopt apps to enhance an established, existing brand name, i.e., grocery stores such as Kroger. Intuitively, app downloads' predictive power should be greater the more important apps are to firms' revenue and earnings generations. We split our sample based on whether apps have in-app purchase options or ad placements and re-estimate the baseline earnings prediction models for the two subsamples. The results are tabulated in Table 3. Noteworthy across both subsamples is the finding that mobile app downloads can predict future performance for all firms, not just for firms that rely on apps as a primary means to generate revenue, but also for firms that employ apps as an alternative product delivery platform. The predictive power of app downloads for future earnings is stronger for in-app revenue firms (point estimates of 0.40 for in-app revenue firms and 0.12 for other firms). The difference in the coefficients is statistically significant at 10%.

3.3 Do Analysts and Investors Fully Recognize Mobile Apps as a Value Driver?

3.3.1 Predicting Future Standardized Unexpected Earnings (SUEs)

Following Lee et al. (2019), we regress standardized unexpected earnings (SUEs) on lagged mobile app downloads. The results are tabulated in Table 4. We define SUEs as the difference between actual earnings and the median of analyst forecasts, scaled by the standard deviation of unexpected earnings over the eight preceding quarters. Analyst forecasts capture the expected earnings by the analysts, thus SUEs capture the unexpected components of earnings not captured by analysts. If analysts have already incorporated the information related to mobile apps in their projection of future earnings, mobile app downloads should not predict future unexpected earnings.

Following Lee et al. (2019), we only include firms with fiscal quarters ending in March, June, September, and December for consistency. Column (1) of Table 4 shows the regression specification with firm fixed effects. The coefficient estimate on mobile app downloads is positive at 5.40 and is statistically significant at the 1% level. Column (2) further includes time fixed effects, and the point estimate on mobile app downloads remains stable at 4.95 and is statistically significant at the 5% level. The point estimates on mobile app downloads remain positive and statistically significant as we sequentially add controls for the firms' lagged SUEs for the past four quarters and lagged R&D, capital investment, and SG&A expenses.

Overall, these results provide evidence that on average analysts do not fully incorporate information embedded in mobile apps in their earnings forecasts, even though mobile apps downloads can predict future earnings (as shown in Tables 2 and 3). As analysts are sophisticated information intermediaries, it is unlikely that they would fail to recognize the importance of mobile apps in generating revenue for all firms. We examine this conjecture In Table 5 by re-estimating the SUE prediction regressions on the two subsamples split based whether apps have in-app purchase options or ad placements. We find that the predictive ability of lagged app downloads for next quarters' SUE disappears for the subsample of firms owning apps with in-app revenue generating features. However, app downloads still strongly predict next quarter's SUE for the subsample of firms owning apps with no in-app revenue generating features. This suggests that while analysts can adequately incorporate the valuation implication of apps in their earnings forecasts when they can readily observe apps' revenue-generating features, they are not able to do so when information on apps' revenue generating ability is not readily available.

3.3.2 Predicting Future Returns

Analysts are sophisticated users of firms' financial information. If analysts fail to fully understand the performance implications of mobile apps for some firms, then it is possible that investors also do not fully incorporate the value of mobile apps into stock prices. We test this possibility by resorting to a portfolio approach. Specifically, we sort all firms into deciles at the beginning of each quarter based on their abnormal mobile app downloads, defined as the difference between log (*DL/AT*) and the average log (*DL/AT*) of the last ten quarters. Using abnormal mobile app downloads ensures that all information is available at the time of portfolio formation and removes firm-specific effects regarding companies' mobile app adoption, which is similar to including firm-fixed effects. These decile portfolios are rebalanced at the beginning of each quarter. We then tabulate the average monthly returns for the three months in the next quarter for each of the ten portfolios.

We present the results in Table 6. Panel A of Table 6 shows the average monthly returns from the lowest (1) to the highest (10) decile portfolios based on lagged abnormal mobile app downloads. In the last row we report the average monthly returns to the hedged long-short strategy based on the difference between the tenth and the first deciles. The average excess returns increase almost monotonically from the lowest lagged abnormal mobile app downloads portfolio to the highest download portfolio, and are generally positive for both the equal-weighted and the value-weighted results. The hedged long-short portfolio yields statistically significant average monthly equal-weighted (value-weighted) excess-returns (H-L) of 98 (74) basis points, which translates into a non-trivial annualized excess return of 12% (9%) per year.

Panel B of Table 6 reports the Fama-MacBeth regression results on the portfolio alphas and factor loadings of the hedged long-short portfolios using the CAPM, the Fama-French 3-factor, 5-factor, and the Fama-French 5-factor plus momentum factor models. All measures of risk factors (*MKTRF*, *SMB*, *HML*, *RMW*, *CMA*, *MOM*) are obtained from the Kenneth French website. The hedged long-short portfolio tends to have a negative loading on the market excess returns (*MKTRF*) and a positive loading on the investment factor (*CMA*). The long-short strategy has relatively small and largely insignificant loadings on the other factors. The alphas of the hedged long-short strategy remain positive and statistically significant after controlling for these factors, suggesting that the return predictability of abnormal mobile app downloads is a distinct phenomenon from the well-documented risk factors.

While the above Fama-MacBeth regression results show that abnormal downloads' predictive ability for future returns cannot be explained by well-documented risk factors, it is still possible that other unobservable risks can drive this result. This would be possible, for example, if abnormal downloads can somehow proxy for firms' discount rate, which would then lead to changes in expected returns. To further ensure that app downloads' predictive ability for future returns is not because of other unobservable risks, we follow a long line of literature and examine the relation between abnormal downloads and subsequent quarter's earnings announcement returns (Bernard and Thomas, 1989; Engelberg et al. 2018; Lee et al. 2020). If investors' biased expectations due to their lack of understanding of mobile apps' value leads to predictable returns, then the return predictability should be stronger around subsequent earnings announcements, as the release of earnings news helps correct prior misconceptions about firms' expected cash flows. If, instead, some unobservable risk is driving return predictability, then subsequent returns should accrue more evenly over subsequent periods.

We regress daily returns surrounding a five-day and seven-day earnings announcement window on lagged abnormal downloads, and compare these earnings announcement window regressions to a baseline regression of daily stock returns on lagged abnormal downloads and report the results in Table 7. The coefficient on lagged abnormal downloads is 0.020 in the baseline regression, whereas the coefficients are 0.281 and 0.210, respectively, in the five-day and seven-day earnings announcement window regressions. The differences between the earnings announcement window coefficients and the baseline regression coefficient are hard to square with a risk explanation. Taken together, both our portfolio approach and earnings announcement window reaction tests indicate that investors do not fully incorporate information embedded in firms' mobile apps.

Are investors better at recognizing the value of mobile apps for some firms versus others? To examine this, we split our sample based on the in-app revenue feature and examine the hedged portfolio returns and portfolio alphas across the two subsamples. Table 8 presents the results. Similar to our findings for SUE predictability, we find that the hedge portfolio returns and alphas are only significant for firms with apps that do not have in-app revenue generating features. The differences in mean hedged portfolio returns and alphas are significant at the 10% level. This set of findings is consistent with our findings for SUE predictability in Table 5: investors appear to be able to price stocks correctly when apps' revenue generating abilities are observable directly via app features, but they are not able to correctly price the stocks when information about apps' ability to generate revenues is not directly available.

3.4 Firm Disclosure and Mobile App Recognition

3.4.1 Measure of Firm Disclosure of Mobile Apps in Regulatory Filings

In the last section, we find that both analysts and investors fail to fully appreciate mobile apps' importance for some app firms, leading to predictable forecast errors and predictable stock returns. In this section, we examine whether firm disclosure of information related mobile apps in SEC filing helps analysts and investors better understand the value of mobile apps and mitigate predictable forecast errors and stock returns. Firm disclosure is immediately available to users upon filing with the SEC, and is the least costly type of information to acquire. We measure firm disclosure of mobile app information by counting relevant phrases ("mobile application", "mobile app", "app", "in-app", "download", "user", "ios", and "android") in 10-Ks, 10-Qs, and 8-Ks. Our resulting mobile app disclosure measure, *MobDis,* is the average mentions of app information across the top three regulatory filings for a given firm in a given year.

Appendix B provides some excerpts of various disclosures included in Bumble and AppLovin's 2022 10-Ks. These three excerpts of 10-Ks all discuss active user counts as a key performance metric and list engagement and retention of existing users and attraction of new users as risk factors in Item 1A. Bumble presents statistics on the number of paying users and total average revenue per paying user in the MD&A, and AppLovin disaggregates revenues into those generated from online software platforms and from apps. Another takeaway from this set of examples is that firms may provide more than just qualitative discussion of their mobile apps; they can also provide useful quantitative information such as the number of active users and revenue generated per app user. Thus, our disclosure measure *MobDis* likely captures the lower bound of the amount of mobile-app related disclosure in firms' regulatory filings, at least for some firms. We note that this measurement issue is unlikely to affect the interpretation of our results as long as firms' total disclosures are positively related to our word count measure.

Before we proceed to the next step, we first examine which kind of firms are more likely to include discussions of mobile apps in their regulatory filings. Intuitively firms that provide more disclosure are likely firms to whom mobile apps are more important, namely firms whose apps have in-app revenue generating features ($1_{inapp>0/ad>0}$). As firms trade off the benefits of disclosure against the costs of disclosure, it is possible that proprietary cost concerns can reduce firms' tendency to disclose app-related information. Prior research finds that firms with a greater amount of proprietary information have incentives to redact customer identities and customer contracts from their 10-Ks (Glaeser 2018). To the extent firms view mobile app related information as proprietary, we may also observe less disclosure from in-app revenue firms.

We present our determinant analysis in Table 9. Panel A presents univariate statistics on the app disclosure measure log (*MobDis+1*) by the indicator variable $1_{inapp>0/ad>0}$. Panel B presents the regression of log (*MobDis+1*) on the indicator variable $1_{inapp>0/ad>0}$, and firm-level measures of proprietary cost concerns using the trade secret measure from Glaeser (2018) (*TrdSecret*) and firms' mark up (*Markup*). In addition, we also include industry competition measures industry price-cost margin *PCM* and three-digit SIC industry concentration ratio *HHI*. We include the same set of control variables for firm characteristics as included in the baseline earnings prediction regression in Table 2. In Column (3) we further include the industry dummies for manufacturing, high-tech, healthcare, and other industries, thus the baseline industry is the consumer industry. Our evidence shows that, *ceteris paribus*, firms disclose more app-related information in their SEC filings the more important mobile apps are to their revenue generations.

3.4.2 SUE and Return Predictability Subsampled by Firm Disclosure

To examine whether firm disclosure helps analysts and investors better incorporate mobile app information in their earnings forecasts, we partition our sample based on the firm disclosure measure log (*MobDis+1*). In particular, we construct a dummy variable $1_{\{dis>median\}}$ that equals one if a firm's disclosure measure is above the sample median in the previous period, and zero otherwise.

Before we proceed, we first present a baseline result of the earnings prediction regressions subsampled by firm disclosure in Table 10. The results show that lagged downloads' predictive ability for future earnings does not vary with the extent of firm disclosure.

We re-estimate the SUE prediction regressions by including an interaction variable between the lagged download measure and the disclosure indicator variable for above sample-median disclosure (log (*DL/AT*)× $1_{\{dis>median\}}$). A negative coefficient on this interaction variable suggests that firm disclosure reduces analyst forecast errors. We also examine the hedged portfolio returns and alphas across the two subsamples. If disclosure facilitates investors' understanding of the value of mobile apps, we should expect to find information embedded in mobile app downloads to be incorporated in prices in a timelier manner, leading to weaker predictable returns.

Table 11 presents the SUE regression results and Table 12 the return predictability results. Table 11 results show that analysts appear to be able to correctly incorporate the valuation implication of mobile apps into their earnings forecasts for firms with greater app-related disclosure, as shown by the significantly negative coefficients on the interaction variable and the insignificance of the sum of the coefficients on log (*DL/AT*) and (log (*DL/AT*)× $1_{\{dis>median\}}$). Table 12 shows that excess returns and alphas are only significant for the subsample of firms with below sample median disclosure. The average hedged long-short strategy return for the below median subsample is 1.35% per month while that of the above median subsample is only 0.31% per month. Adjusting for the Fama-French 5-factor model leads to the same conclusion – the alpha of the hedged long-short strategy for the below median subsample is 1.65% per month, while it is only 0.60% for the above median subsample. These results suggest that firm disclosure helps investors better incorporate information about mobile apps in valuing the stocks, leading to smaller predictable returns.

Taken together, the results in Table 10 which shows apps' predictive ability for earnings does not vary with firm disclosure, in combination with the results from Tables 11 and 12 which shows that firm disclosure helps both analysts and investors, highlights the importance of information availability to the investing public.

4 Conclusion

Mobile apps are becoming an integral part of our daily lives and are increasingly being adopted by firms to facilitate their revenue generations. Globally annual mobile app downloads have increased 10-fold from a little under 14 billion in 2012 to over 142 billion in 2021. Industry practitioners actively track app downloads and firms themselves pay close attention mobile app downloads as a useful indicator to predict future growth. However, accounting research appears to lag behind in understanding mobile apps and their importance to firms. We move toward bridging this gap by studying mobile app downloads as a leading performance indicator, and by examining whether the investment community at large understands the importance of mobile apps.

We document three sets of results. First, we show that lagged mobile app downloads significantly predict future earnings, above and beyond firm size, book-to-market, current earnings, R&D expenditure, capital investments, SG&A expenses, and various intangible asset accounts. Notably mobile app downloads can predict future performance not just for firms that rely heavily on apps to generate revenue (e.g., apps with in-app purchase option or ad placements), but also for other more traditional firms that adopt mobile apps as an alternative means to deliver products (e.g., McDonald's, Walmart). Second, we document that lagged mobile app downloads significantly predict subsequent analyst forecast errors, and that lagged abnormal downloads significantly predict future returns, suggesting that analysts and investors fail to fully appreciate the valuation implications of mobile apps. Cross-sectional analysis shows that this lack of understanding resides primarily with firms owning apps that do not have in-app revenue generating features. Third, we find that firm discussion of mobile-app related information in the top three SEC filings (10-K, 10-Q, and 8-K) significantly mitigates the predictive ability of mobile app downloads for subsequent analyst forecast errors and future returns.

Taken together, our results suggest that while mobile app downloads are a leading performance indicator, neither analysts nor investors appear to fully understand the valuation implication of mobile apps. Importantly, we find that relevant information, including firms' disclosure on mobile apps in regulatory filings, can mitigate analysts' forecast errors and investors' mispricing of firms' stocks.

Our findings have important implications for researchers, regulators, and the investment community in general. We hope our study will generate more research to enhance our collective understanding of the new performance indicators of the digital economy.

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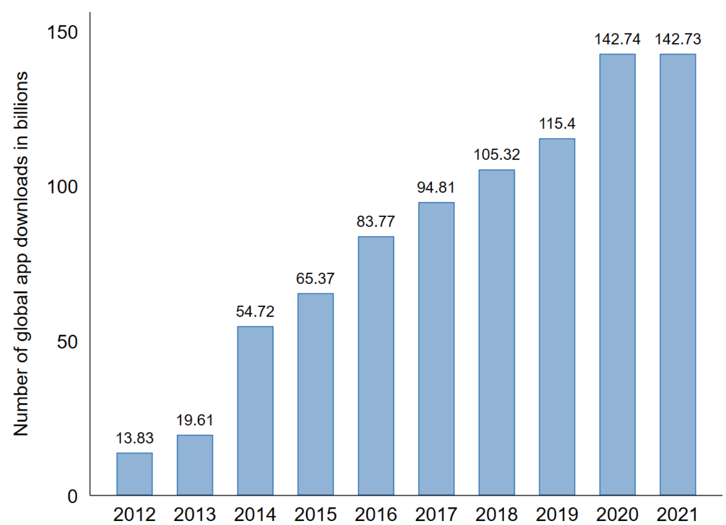
Figure 1: Mobile App Downloads Over Time
(in billions)

This figure shows the yearly number of Mobile App downloads. Panel A presents the yearly global number of Mobile App downloads for both iOS and Android combined. Panel B presents the yearly number of Mobile App downloads in the sample for both iOS and Android combined.

(a) Worldwide Downloads



(b) Downloads in Sample

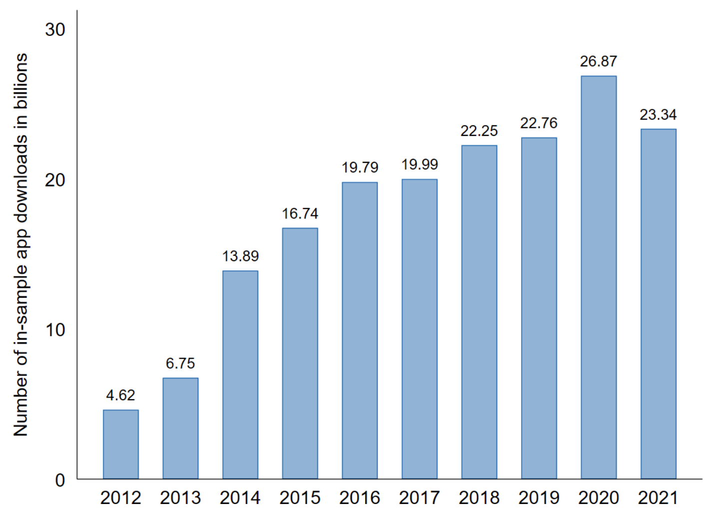


Table 1: Summary Statistics

This table reports the summary statistics of the sample and variables used in this paper. Panel A compares the sample composition used in the paper and the full Compustat sample for each of the Fama-French 5 industry. Panel B reports the mean, standard deviation, and distribution of the main variables used in the paper. Panel C reports the correlation across the main variables, and bold font indicates significant at the 5% level.

Panel A: FF 5 industry	Compustat sample				app sample				
	FFI	Freq.	Percent	Cum.	FFI	Freq.	Percent	Cum.	ratio
Consumer	1	956	10.32	10.32	1	211	25.27	25.27	211/956=0.22
Manufacturing	2	1,055	11.39	21.71	2	103	12.34	37.6	0.10
High Tech	3	1,664	17.96	39.67	3	281	33.65	71.26	0.17
Health	4	1,573	16.98	56.64	4	48	5.75	77.01	0.03
Other	5	4,017	43.36	100	5	192	22.99	100	0.05
Total	Total	9,265	100		Total	835	100		835/9265=0.09

Panel B	Mean	SD	25%	50%	75%
DL (in thousands)	4745.77	23046.84	2.71	70.66	650.74
$\log(DL/AT)$	2.88	2.76	0.26	2.19	4.80
$\log(DL/AT)^{ab}$	0.06	0.43	-0.15	-0.06	0.13
MobDis	18.5	38.41	1.06	2.30	11.35
$\log(MobDis+1)$	1.76	1.40	0.72	1.20	2.51
$1_{inapp>0\|ad>0}$	0.20	0.40	0	0	0
SALE/AT (%)	23.04	19.42	10.75	17.22	29.60
NI/AT (%)	0.90	3.50	0.16	1.11	2.34
AT (in mils)	50249	191152	1651	5702	22432
$\log(AT)$	8.74	2.00	7.41	8.65	10.02
RD/AT (%)	0.97	1.77	0.00	0.00	1.37
CAPX/AT (%)	0.97	1.07	0.30	0.64	1.28
SUE ($\times$100)	78.47	186.51	0.00	58.36	152.95

Panel C	$\log(DL/AT)$	$\log(DL/AT)^{ab}$	SALE/AT	NI/AT	$\log(AT)$	RD/AT	CAPX/AT	SUE	$\log(MobDis+1)$	$1_{inapp>0\|ad>0}$
$\log(DL/AT)$	1.00									
$\log(DL/AT)^{ab}$	**0.11**	1.00								
SALE/AT (%)	**0.13**	**0.11**	1.00							
NI/AT (%)	**-0.05**	**0.08**	**0.16**	1.00						
$\log(AT)$	**-0.37**	-0.05	**-0.36**	**0.13**	1.00					
RD/AT (%)	**0.24**	0.00	0.00	**-0.18**	**-0.32**	1.00				
CAPX/AT (%)	**0.13**	**0.10**	**0.22**	**0.04**	**-0.16**	0.02	1.00			
SUE ($\times 100$)	-0.02	-0.02	0.01	**0.12**	0.02	**0.11**	**-0.06**	1.00		
$\log(MobDis+1)$	**0.48**	**-0.06**	-0.07	**-0.10**	**-0.22**	**0.44**	-0.03	0.06	1.00	
$1_{inapp>0\|ad>0}$	**0.47**	**-0.09**	**-0.10**	0.00	0.02	**0.12**	-0.02	0.00	**0.32**	1.00

Table 2: Predicting Future Earnings

This table reports the regression results of earnings on lagged mobile app downloads. Standard errors are clustered at the firm level and shown in parentheses. Variable definitions are presented in the Appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A VARIABLES	(1) NI/AT_q	(2) NI/AT_q	(3) NI/AT_q
$\log(DL/AT)_{q-1}$	0.20***	0.17***	0.16**
	(0.06)	(0.05)	(0.06)
$\log(AT)_{q-1}$	0.23	0.10	-0.07
	(0.16)	(0.13)	(0.14)
NI/AT_{q-1}		0.22***	0.18***
		(0.02)	(0.03)
BM_{q-1}			-1.93***
			(0.19)
RD/AT_{q-1}			-0.13**
			(0.06)
$CAPX/AT_{q-1}$			0.12***
			(0.04)
SGA/AT_{q-1}			-0.03
			(0.02)
Constant	-1.65	-0.55	2.03
	(1.47)	(1.17)	(1.34)
Firm FE	Y	Y	Y
Time FE	Y	Y	Y
Observations	25,343	25,335	18,260
R-squared	0.47	0.50	0.51

Panel B	(1)	(2)	(3)	(4)
VARIABLES	NI/AT_q	NI/AT_q	NI/AT_q	NI/AT_q
$\log(DL/AT)_{q-1}$	0.15**	0.15**	0.16**	0.16**
	(0.06)	(0.06)	(0.06)	(0.06)
$\log(AT)_{q-1}$	0.03	0.04	-0.15	-0.05
	(0.16)	(0.17)	(0.15)	(0.17)
NI/AT_{q-1}	0.18***	0.18***	0.17***	0.17***
	(0.03)	(0.03)	(0.03)	(0.03)
BM_{q-1}	-1.94***	-1.94***	-1.97***	-1.99***
	(0.19)	(0.19)	(0.20)	(0.20)
RD/AT_{q-1}	-0.12**	-0.12**	-0.14**	-0.13**
	(0.06)	(0.06)	(0.06)	(0.06)
$CAPX/AT_{q-1}$	0.13***	0.13***	0.11**	0.11**
	(0.04)	(0.04)	(0.04)	(0.04)
SGA/AT_{q-1}	-0.03	-0.03	-0.04*	-0.04*
	(0.02)	(0.02)	(0.02)	(0.02)
$INTAN/AT_{q-1}$	-0.01**			-0.01**
	(0.00)			(0.00)
SFT/AT_{q-1}		-0.02		
		(0.04)		
GW/AT_{q-1}		-0.01*		
		(0.01)		
$INTANO/AT_{q-1}$		-0.01		
		(0.01)		
Q^{tot}_{q-1}			0.06***	0.06**
			(0.02)	(0.02)
Constant	1.40	1.32	2.63*	2.07
	(1.46)	(1.49)	(1.40)	(1.52)
Firm & Time FEs	Y	Y	Y	Y
Observations	18,260	18,260	17,523	17,523
R-squared	0.51	0.51	0.50	0.50

Table 3: Predicting Future Earnings – Subsample by In-app Purchase Option/Ad

This table reports the regression results of earnings on lagged mobile app downloads, subsampled by whether apps have in-app purchase options or ad placements. Standard errors are clustered at the firm level and shown in parentheses. Variable definitions are presented in the Appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)
VARIABLES	NI/AT_q	NI/AT_q	NI/AT_q	NI/AT_q
	No In-App/Ad		In-App/Ad	
$\log(DL/AT)_{q-1}$	0.15**	0.12**	0.44**	0.40**
	(0.07)	(0.05)	(0.18)	(0.18)
$\log(AT)_{q-1}$	0.30	0.13	0.11	0.05
	(0.20)	(0.16)	(0.29)	(0.27)
NI/AT_{q-1}		0.23***		0.16***
		(0.02)		(0.04)
Firm FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Observations	20,387	20,384	4,956	4,951
R-squared	0.50	0.53	0.40	0.41
Coeff diff				(4) - (2)
p-value				0.082

Table 4: Predicting Future SUE

This table reports regression results of SUE (standardized unexpected earnings) on lagged mobile app downloads. Standard errors are clustered at the firm level and shown in parentheses. Variable definitions are presented in the Appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(DL/AT)_{q-1}$	5.40***	4.95**	5.01***	5.07***	4.76***	4.16**
	(1.95)	(2.08)	(1.67)	(1.79)	(1.79)	(1.95)
SUE_{q-1}			11.83***	10.99***	12.33***	11.44***
			(0.80)	(0.82)	(0.87)	(0.90)
SUE_{q-2}			3.00***	3.17***	3.46***	3.80***
			(0.75)	(0.76)	(0.82)	(0.83)
SUE_{q-3}			1.72**	1.36*	1.93**	1.68**
			(0.70)	(0.70)	(0.76)	(0.76)
SUE_{q-4}			0.50	0.58	0.46	0.59
			(0.64)	(0.65)	(0.70)	(0.71)
RD/AT_{q-1}					0.32	-1.30
					(3.22)	(3.32)
$CAPX/AT_{q-1}$					-4.02*	-0.36
					(2.43)	(2.46)
SGA/AT_{q-1}					-0.59	1.09
					(0.93)	(0.96)
Constant	64.07***	65.28***	52.30***	52.85***	59.94***	49.52***
	(5.23)	(5.59)	(4.63)	(4.88)	(6.58)	(6.64)
Firm FE	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y
Observations	19,938	19,938	19,322	19,322	16,378	16,378
R-squared	0.14	0.17	0.16	0.19	0.16	0.20

Table 5: Predicting Future SUE – Subsample by In-app Purchase /Ad

This table reports regression results of SUE (standardized unexpected earnings) on lagged mobile app downloads, subsampled by in-app purchase /ad. Standard errors are clustered at the firm level and shown in parentheses. Control 1 includes firms' lagged SUEs for the past four quarters. Control 2 further includes firms' lagged R&D, capital investment ratios, and SG&A. Full interaction terms with $1_{inapp>0/ad>0}$ are included in the regressions. Variable definitions are presented in the Appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)
	SUE_q	SUE_q	SUE_q
$\log(DL/AT)_{q-1}$	4.76*	5.92***	5.07**
	(2.53)	(2.18)	(2.33)
$\log(DL/AT)_{q-1} \times 1_{inapp>0\mid ad>0}$	-1.09	-4.87	-5.77
	(6.44)	(5.25)	(6.20)
Firm FE	Y	Y	Y
Time FE	Y	Y	Y
Controls	N	Control 1	Control 2
Observations	19,905	19,293	16,351
R-squared	0.18	0.19	0.20

Table 6: Portfolio Returns

This table reports decile portfolio returns sorted on lagged abnormal mobile app downloads. Panel A reports the average portfolio returns and Panel B reports the factor loadings of the hedged long-short strategy returns using Fama-MacBeth regressions. 1-10 are the decile portfolio excess returns from the lowest decile to the highest portfolios. H-L is the long-short strategy returns that long the decile with the highest lagged abnormal download and short the decile with the lowest lagged abnormal download. EW is equal-weighted and VW is value-weighted. The alphas in Panel A are calculated using the Carhart 4-factor model. The benchmark factor models used in Panel B include CAPM, Fama-French 3- factor, Carhart 4-factor, Fama-French 5-factor, and the Fama-French 5-factor plus momentum fac- tor models. Variable definitions are presented in the Appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A: Portfolio Sorting				
%	EW		VW	
	Mean	Alpha	Mean	Alpha
Low	0.93	-0.25	0.70	-0.51*
	(0.70)	(0.32)	(0.58)	(0.31)
2	1.10*	-0.02	0.69	-0.33
	(0.58)	(0.22)	(0.48)	(0.26)
3	1.16*	-0.01	1.09**	-0.12
	(0.59)	(0.17)	(0.49)	(0.18)
4	0.87	-0.24	1.05*	-0.17
	(0.55)	(0.16)	(0.53)	(0.19)
5	1.12**	0.04	0.84*	-0.13
	(0.56)	(0.15)	(0.42)	(0.19)
6	1.21**	0.21	1.19***	0.24
	(0.53)	(0.17)	(0.45)	(0.24)
7	1.43**	0.29	1.18**	0.10
	(0.56)	(0.22)	(0.48)	(0.21)
8	1.38***	0.34*	1.25***	0.17
	(0.52)	(0.18)	(0.45)	(0.18)
9	1.46**	0.38*	1.51***	0.49**
	(0.56)	(0.21)	(0.46)	(0.22)
High	1.91***	1.09***	1.44***	0.43**
	(0.64)	(0.34)	(0.43)	(0.20)
H-L	0.98***	1.25***	0.74*	0.89**
	(0.35)	(0.34)	(0.40)	(0.38)

Panel B: Factor Loadings

EW	H-L	H-L	H-L	H-L	H-L	VW	H-L	H-L	H-L	H-L	H-L
α	1.25***	1.35***	1.25***	1.21***	1.08***	α	0.99**	0.94**	0.89**	0.66*	0.58*
	(0.35)	(0.34)	(0.34)	(0.34)	(0.33)		(0.40)	(0.38)	(0.38)	(0.35)	(0.35)
MKTRF	-0.25***	-0.29***	-0.21**	-0.27***	-0.19**	MKTRF	-0.23**	-0.15	-0.11	-0.10	-0.04
	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)		(0.09)	(0.09)	(0.10)	(0.09)	(0.09)
SMB		0.15	0.20	0.25*	0.34**	SMB		-0.38***	-0.36**	-0.21	-0.15
		(0.13)	(0.13)	(0.15)	(0.14)			(0.14)	(0.14)	(0.15)	(0.15)
HML		0.13	0.27**	-0.04	0.10	HML		0.33***	0.40***	-0.03	0.06
		(0.10)	(0.11)	(0.12)	(0.13)			(0.11)	(0.12)	(0.13)	(0.13)
RMW				0.24	0.33*	RMW				0.39*	0.44**
				(0.20)	(0.19)					(0.20)	(0.20)
CMA				0.40*	0.42**	CMA				0.89***	0.90***
				(0.21)	(0.21)					(0.22)	(0.22)
MOM			0.29***		0.32***	MOM			0.15		0.20*
			(0.11)		(0.11)				(0.12)		(0.11)
Observations	93	93	93	93	93	Observations	93	93	93	93	93
R-squared	0.10	0.15	0.21	0.19	0.27	R-squared	0.07	0.18	0.19	0.34	0.36

Table 7: Returns on Earnings Announcement Days

This table reports regressions of firms' daily stock returns in a quarter on the previous quarter's $\log(DL/AT)^{ab}$ using the whole sample and the samples of the 5-day and 7-day windows around the firms' earnings announcement dates. For the baseline result, all trading days are included. For the 5-day and 7-day results, only trading days around the 5-day and 7-day of the firms' earnings announcement dates are included in the regressions, respectively. Results are based on the Fama-MacBeth regression method. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)
	Baseline	5-day	7-day
$\log(DL/AT)^{ab}$	0.020**	0.281*	0.210***
	(0.008)	(0.164)	(0.081)
Obs	1,083,128	49,283	82,138

Table 8: Predicting Future Returns – Subsample by In-app Purchase /Ad

This table reports the regression results of hedged long-short portfolio returns and portfolio alphas, subsampled by in-app purchase/ad. Standard errors are shown in parentheses. Variable definitions are presented in the Appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Mean	Alpha	Mean	Alpha
	(1)	(2)	(3)	(4)
	No In-App/Ad		In-App/Ad	
H-L	0.85**	1.06***	-0.52	-0.22
	(0.41)	(0.40)	(0.79)	(0.74)
Mean Diff			(3) - (1)	(4) - (2)
p-value			0.065	0.060

Table 9: Determinant Model of Mobile App Disclosure in SEC Filings

This table reports regression results of firms' mobile app disclosure measure. The dependent variable is the logged mobile app disclosure measure $\log(MobDis+1)$. *MobDis* is measured as the average word mention of app-related information over the top three SEC filings, 10-K, 10-Q, and 8-Ks.Year fixed effects are included. Standard errors are clustered at the firm level and show in parentheses. Manuf, HiTec, Hlth, and Other are dummy variables of manufacturing, high tech, health, and other industry, respectively, according to Fama-French 5 industry definition. The omitted group is the consumer industry from the Fama-French 5 industry. Variable definitions are presented in the Appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A: Summary of $\log(MobDis+1)$			
Mean	SD	Mean	SD
$1_{inapp>0\|ad>0} = 1$		$1_{inapp>0\|ad>0} = 0$	
2.28	1.41	1.65	1.37

Panel B: Determinant Model			
	(1)	(2)	(3)
$1_{inapp>0\|ad>0}$	0.50***	0.44***	0.36***
	(0.07)	(0.07)	(0.07)
SALE/AT		-0.00**	-0.00
		(0.00)	(0.00)
$\log(SIZE)$		-0.03**	-0.02
		(0.01)	(0.01)
BM		0.01	0.02
		(0.06)	(0.06)
RD/AT		0.14***	0.13***
		(0.02)	(0.02)
CAPX/AT		-0.05**	-0.05**
		(0.02)	(0.02)
SGA/AT		0.00	0.01
		(0.00)	(0.00)
TrdSecret		0.14***	0.10**
		(0.04)	(0.04)
Markup		-0.12	-0.09
		(0.12)	(0.11)
PCM		0.25*	0.28**
		(0.14)	(0.13)
HHI		-0.32***	-0.26***
		(0.09)	(0.10)
Manuf			0.12*
			(0.07)
HiTec			0.26***
			(0.08)
Hlth			-0.33***
			(0.09)
Other			0.05
			(0.06)
Obs	5,999	4,832	4,832
R-squared	0.66	0.72	0.73

Table 10: Predicting Future Earnings – Subsample by Firm Disclosure Measure

This table reports regression results of earnings on lagged mobile app downloads, subsampled by the median value of mobile app disclosure measure in firms 10-K, 10-Qs, and 8-Ks. Standard errors are clustered at the firm level and shown in parentheses. Controls include lagged logged total asset and lagged NI/AT. Full interaction terms with $1_{\{dis>median\}}$ are included in the regressions. Variable definitions are presented in the Appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

VARIABLES	NI/AT_q	NI/AT_q
$\log(DL/AT)_{-1}$	0.21***	0.16**
	(0.08)	(0.07)
$\log(DL/AT)_{-1} \times 1_{\{dis>median\}}$	-0.02	0.01
	(0.10)	(0.10)
Firm FE	Y	Y
Time FE	Y	Y
Controls	N	Y
Observations	21,938	21,932
R-squared	0.49	0.51

Table 11: Predicting Future SUE – Subsampled by Firm Disclosure Measure

This table reports regression results of SUE (standardized unexpected earnings) on lagged mobile app downloads, subsampled by the median value mobile app disclosure measure in firms 10-K, 10-Qs, and 8-Ks. Standard errors are clustered at the firm level and shown in parentheses. Control 1 includes firms' lagged SUEs for the past four quarters. Control 2 further includes firms' lagged R&D, capital investment ratios, and SG&A. Full interaction terms with $1_{\{dis>median\}}$ are included in the regressions. Variable definitions are presented in the Appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

VARIABLES	(1)	(2)	(3)
$\log(DL/AT)_{-1}$	9.48***	9.23***	9.49***
	(3.55)	(3.28)	(3.53)
$\log(DL/AT)_{-1} \times 1_{\{dis>median\}}$	-8.79*	-7.95*	-11.82**
	(4.65)	(4.26)	(4.57)
Firm & Time FE	Y	Y	Y
Controls	N	Control 1	Control 2
Observations	17,884	17,559	15,277
R-squared	0.20	0.21	0.22

Table 12: Predicting Future Returns – Subsampled by Firm Disclosure Measure

This table reports the regression results of hedged long-short portfolio returns and portfolio alphas, subsampled by the median value of mobile app disclosure measure in firms 10-K, 10-Qs, and 8-Ks. Standard errors are shown in parentheses. Variable definitions are presented in the Appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	No In-App/Ad		In-App/Ad	
	$1_{\{dis<median\}}$		$1_{\{dis\geq median\}}$	
	Mean	Alpha	Mean	Alpha
	(1)	(2)	(3)	(4)
H-L	1.35***	1.63***	0.31	0.64
	(0.45)	(0.47)	(0.40)	(0.39)
Mean Diff			(3) - (1)	(4) - (2)
p-value			0.096	0.083

Appendix

Appendix A: Variable definitions

Variable	Description	Source
$\log(DL/AT)$	logged quarterly Mobile App downloads divided by last quarter's firm total asset.	ST/WRDS
$\log(DL/AT)^{ab}$	$\log(DL/AT)$ minus the mean of the last ten quarters' $\log(DL/AT)$.	ST/WRDS
SALE/AT	quarterly revenue divided by last quarter's firm total asset.	WRDS
NI/AT	quarterly net income divided by last quarter's firm total asset.	WRDS
$\log(AT)$	logged firm total asset.	WRDS
RD/AT	quarterly R&D expense divided by last quarter's firm total asset.	WRDS
CAPX/AT	quarterly capital expenditure divided by last quarter's firm total asset.	WRDS
INTAN/AT	intangible asset divided by last quarter's firm total asset.	WRDS
SFT/AT	capitalized software divided by last quarter's firm total asset.	WRDS
GW/AT	good will divided by last quarter's firm total asset.	WRDS
INTANO/AT	other intangible asset divided by last quarter's firm total asset.	WRDS
Q^{tot}	total Q measure as in Peters and Taylor (2016).	WRDS
SUE	standardized unexpected earnings constructed as the difference between actual earnings and the median of analyst forecasts, scaled by the standard deviation of unexpected earnings over the eight preceding quarters.	WRDS
MKTRF	the market excess return from the Kenneth French website.	Kennth French Website
SMB	the size factor from the Kenneth French website.	Kennth French Website
HML	the value factor from the Kenneth French website.	Kennth French Website
RMW	the profitability factor from the Kenneth French website.	Kennth French Website
CMA	the investment factor from the Kenneth French website.	Kennth French Website
MOM	the momentum factor from the Kenneth French website.	Kennth French Website
Mobile App disclosure measure (*MobDis*)	the average mentions of app information across firms' 10-Ks, 10-Qs, and 8-Ks, the top three regulatory filings for a given firm in a given year. The phrases include "mobile application", "mobile app", "app", "in-app", "download", "user", "ios", and "android".	EDGAR
$1_{inapp>0 \| ad>0}$	indicator variable that equals one if the company has at least one app that has in-app purchase options or at least one app that serves advertisement in a given year, and zero otherwise.	Hand Collected ST

Variable	Description	Source
Markup	firm-level markup is calculated as the quarterly revenue divided by the difference between quarterly revenue and quarterly net income.	WRDS
PCM	industry price cost margin is calculated as the $\frac{sale-cogs+\Delta invt}{sale+\Delta invt}$, where *sale* is the quarterly industry revenue, *cogs* is the quarterly industry cost of good sold, and *invt* is the quarterly industry inventory. Industry is defined as the three-digit SIC industry.	WRDS
HHI	industry HHI at the three-digit SIC level. HHI is calculated as the sum of the squared quarterly revenue shares of each firm in the industry.	WRDS

Appendix B: 10-K Mobile App Related Disclosures

A. Bumble Inc. 2022 10-K

Item 1. Business

Who We Are

Bumble app was founded because we noticed two different, yet related issues in our society: antiquated gender norms, and a lack of kindness and accountability on the internet. We observed that women were often treated unequally in society, especially in romantic relationships. At the same time, social networks created possibilities for connections, but they were focused on connections with people you already know and lacked guardrails to encourage better behavior online.

We created Bumble app to change this. The Bumble brand was built with women at the center—where women make the first move. Our platform is designed to be safe and empowering for women, and, in turn, provides a better environment for everyone. We are leveraging innovative technology solutions to create a more inclusive, safe and accountable way to connect online for all users regardless of gender.

Bumble's mission is to create a world where all relationships are healthy and equitable, through Kind Connections. Our platform enables people to connect and build healthy and equitable relationships on their own terms. We focus on building authenticity and safety in the online space, which is marked at times by isolation and toxicity. We also believe there is a significant opportunity to extend our platform beyond online dating into healthy relationships across all areas of life: love, friendships, careers and beyond. By empowering women across all of their relationships, we believe that we have the potential to become a preeminent global women's brand.

In 2022, we operated three apps, Bumble app, Badoo app and Fruitz app, where during 2022, on average, over 40 million users came on a monthly basis to discover new people and connect with each other in a safe, secure and empowering environment. Bumble app, Badoo app and Fruitz app monetize via a freemium model, where the use of the service is free and a subset of the users pay for subscriptions or in-app purchases to access premium features. We are a leader in the online dating space, which has become increasingly popular over the last decade and has been cited as the most common way for new couples to meet in the United States.

The Bumble and Badoo apps ranked among the top five grossing iOS lifestyle apps in 109 and 99 countries, respectively, as of December 31, 2022.

- Bumble app, launched in 2014, is one of the first dating apps built with women at the center. On Bumble app, women make the first move. Bumble app is a leader in the online dating sector across several countries, including the United States, United Kingdom, Australia and Canada. We had approximately 2.0 million Bumble App Paying Users during the year ended December 31, 2022.
- Badoo app, launched in 2006, was one of the pioneers of web and mobile free-to-use dating products. Badoo app's focus is to make finding meaningful connections easy, fun and accessible for a mainstream global audience. Badoo app continues to be a market leader in Europe and Latin America. We had approximately 1.2 million Badoo App and Other Paying Users during the year ended December 31, 2022.

Our Technology Has Transformed Online Dating

Technology is at the core of what differentiates our platform. We have a global team of software engineers and product managers who drive the development of our platform. We release live updates rapidly, often once a week to our mobile app and twice a day to our server backend, allowing us to run dozens of tests simultaneously across the entire audience. The rapid nature of our testing framework allows us to optimize the user experience. Our technology and product teams work hand in hand from ideation to product launch, and this has allowed us to be at the forefront of releasing features geared towards improving the safety of our community.

Our technology platform is fueled by:

- **Shared infrastructure**: Our apps share some common infrastructure, which allows insights to be shared between apps. This allows us to quickly test new features, provides us with flexibility to migrate features from one app to another where appropriate, and improves execution at scale by driving faster improvements in our apps, while simultaneously driving operating efficiencies by reducing the cost of launching new features. Given our shared infrastructure, we can also innovate and scale efficiently as we enter new geographies and new categories outside online dating. Moreover, in seeking to acquire companies, we look for opportunities to leverage our shared infrastructure (for example, our content moderation capabilities) to accelerate their product roadmap.
- **Our data and machine learning capabilities**: We are continually analyzing data from user interactions on our platform, allowing us to constantly optimize the user experience. We have machine and deep learning capabilities that we leverage to personalize the potential matches we display, inform our product pipeline and otherwise tailor the experience for specific users. Our machine and deep learning capabilities plays a key role in identity fraud prevention as well as blocking inappropriate behavior and content from polluting our platform.
- **Our data protection and privacy standards**: We are both committed and mandated to adhere to strict privacy standards.

Item 1A. Risk Factors

You should carefully consider the following risks and all of the other information set forth in this Annual Report, including without limitation "Item 7—Management's Discussion and Analysis of Financial Condition and Results of Operations" and our consolidated financial statements and related notes in "Item 8—Financial Statements and Supplementary Data." The following risk factors have been organized by category for ease of use; however, many of the risks may have impacts in more than one category.

Risks Related to Our Brand, Products and Operations

If we fail to retain existing users or add new users, or if our users decrease their level of engagement with our products or do not convert to paying users, our revenue, financial results and business may be significantly harmed.

The size of our user base and our users' level of engagement are critical to our success. Our apps monetize via a freemium model where the use of our service is free and a subset of our users pay for subscriptions or in-app purchases to access premium features. Our financial performance has thus been and will continue to be significantly determined by our success in adding, retaining and engaging users of our products and converting users into paying subscribers or in-app purchasers. We expect that the size of our user base will fluctuate or decline in one or more markets from time to time, including if users find meaningful relationships on our platforms and no longer need to engage with our products. Furthermore, if people do not perceive our products to be useful, reliable, and/or trustworthy, we may not be able to attract or retain users or otherwise maintain or increase the frequency and duration of their engagement. A number of other online dating companies that achieved early popularity have since experienced slower growth or declines in their user bases or levels of engagement. There is no guarantee that we will not experience a similar erosion of our user base or engagement levels. User engagement can be difficult to measure, particularly as we introduce new and different products and services. Any number of factors can negatively affect user retention, growth, and engagement, including if:

Item 7. Management's Discussion and Analysis of Financial Condition and Results of Operations

Key Operating Metrics

We regularly review a number of metrics, including the following key operating metrics, to evaluate our business, measure our performance, identify trends in our business, prepare financial projections and make strategic decisions. We believe these operational measures are useful in evaluating our performance, in addition to our financial results prepared in accordance with GAAP. Refer to the section "Certain Definitions" at the beginning of this Annual Report for the definitions of our Key Operating Metrics.

The following metrics were calculated excluding paying users and revenue generated from Fruitz:

(in thousands, except ARPPU)	Year Ended December 31, 2022	Year Ended December 31, 2021	Year Ended December 31, 2020
Key Operating Metrics			
Bumble App Paying Users	2,002.2	1,499.8	1,142.1
Badoo App and Other Paying Users	1,179.7	1,394.1	1,363.4
Total Paying Users	3,181.9	2,893.9	2,505.5
Bumble App Average Revenue per Paying User	$ 28.90	$ 29.37	$ 26.14
Badoo App and Other Average Revenue per Paying User	$ 13.06	$ 13.13	$ 12.66
Total Average Revenue per Paying User	$ 23.03	$ 21.55	$ 18.81

B. AppLovin Corporation 2022 10-K

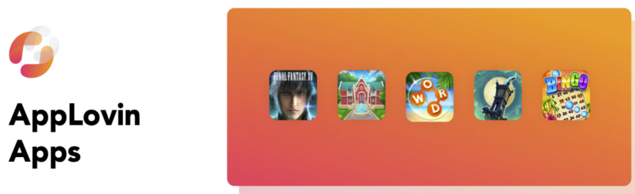
Item 1. Business

In 2018, given an opportunity to scale our own apps using our Software Platform, insights, and expertise in the mobile app ecosystem, we launched AppLovin Apps (Apps). Today, our Apps consist of a globally diversified portfolio of over 350 free-to-play mobile games across five genres, run by eleven studios including studios that we own (Owned Studios) and others that we partner with (Partner Studios). Our studios generally focus on the development of easy to learn and play games, which appeal to a broad range of demographics, but also develop several games for other genres.

We generate our revenue from our Software Platform and Apps. As more developers use our Software Platform to market and monetize their mobile apps, we gain access to more users and more user engagement further strengthening our scaled distribution. As our distribution grows, we gain better insights for our App Graph and AXON recommendation engine, which then further enhances our Software Platform.

We accelerate our capabilities and enhance our strategic position by actively pursuing acquisitions and partnerships for new technologies and apps. From the beginning of 2018 through 2022, we have invested nearly $4.0 billion across 29 strategic acquisitions and partnerships with app studios, games, and software platforms.

AppLovin Apps



Today, our Apps consist of a globally diversified portfolio of over 350 free-to-play mobile games across five genres, run by eleven studios located worldwide with a deep bench of talented developers. Our Owned Studios and Partner Studios have developed and published games across a number of genres including: casual, hypercasual, match-three, midcore, and card/casino. Our Apps contribute a highly predictable and diversified stream of revenue which we leverage to invest into acquiring more users and driving continued growth.

A diverse portfolio allows us to reach multiple user demographics and diversify our mobile game development across many different genres. We have a broad audience on our Apps and this allows our Software Platform to connect users to a wide range of content. A large segment of our portfolio is casual games which have a lower risk of development and generally have more predictable revenue streams and return on investments. Casual games can be played a few minutes at a time and appeal to a wide range of users across many highly attractive demographics.

Our Owned Studios and Partner Studios leverage live ops to quickly iterate and increase in-game monetization by optimizing app economies and improving in-game conversion on items and offers. Our Software Platform and expertise provide analytical tools, testing capabilities, and other solutions such as distributed development, competitive insights, localizations resources, creative services to develop and test ads and resource centers to access design and development expertise.

We also provide a set of services that help both our Apps and third-party developers optimize their games and leverage our expertise to better streamline their business operations.

ITEM 1A. RISK FACTORS

If we fail to retain existing users or add new users cost-effectively, or if our users decrease their level of engagement with Apps, our business, financial condition, and results of operations could be adversely affected.

The size of our user base and the level of user engagement with our Apps are critical to our success. Our results of operations have been and will continue to be significantly determined by our success in acquiring and engaging App users. We expect that the number of our App users may fluctuate or decline as a result of apps divestitures or other actions we take in connection with our review of our Apps portfolio, or in one or more markets from time to time, particularly in markets where we have achieved higher penetration rates or where the macro economic conditions have been negatively impacted. For example, we have reduced our user acquisition spend for our portfolio of Apps as we increased our desired return goals, which has contributed to a decline in MAPs compared to periods before such adjustments. In addition, if people do not perceive our Apps as useful or entertaining, we may not be able to attract or retain users or otherwise maintain or increase the frequency and duration of their engagement, which could harm our revenue. A number of mobile apps that achieved early popularity have since seen their user bases or user engagement levels decline. There is no guarantee that we will not experience a similar erosion of our App users or user engagement levels. Our user engagement patterns have changed over time, and user engagement can be difficult to measure, particularly as we introduce new and different Apps. Any number of factors can adversely affect user growth and engagement, including if:

- users increasingly engage with mobile apps offered by competitors or mobile apps in categories other than those of our Apps;
- we fail to introduce new Apps or features that users find engaging or that achieve a high level of market acceptance or we introduce new Apps, or make changes to existing Apps that are not favorably received;
- users feel that their experience is diminished as a result of the decisions we make with respect to the frequency, prominence, format, size, and quality of advertisements that we display;
- users have difficulty installing, updating, or otherwise accessing our Apps as a result of actions by us or third parties;
- we are unable to continue to develop Apps that work with a variety of mobile operating systems and networks; and
- questions about the quality of our Apps, our data practices or concerns related to privacy and sharing of personal information and other user data, safety, security, or other factors.

14. Segments and Geographic Information

During the second quarter of 2022, the Company revised the presentation of segment information to align with changes to how the Company's chief operating decision maker (“CODM”) manages the business, allocates resources and assesses operating performance. The CODM is the Company's Chief Executive Officer. Prior to the second quarter of 2022, the Company had a single operating and reportable segment. Beginning in the second quarter of 2022, the Company reports operating results based on two reportable segments: Software Platform and Apps. As of December 31, 2022, the Company's operating segments are the same as the reportable segments, which are as follows:

- *Software Platform:* Software Platform generates revenue prim$arily from fees paid by advertisers for the placement of ads on mobile applications owned by Publishers.
- *Apps:* Apps generates revenue when a user of one of the Apps makes an in-app purchase ("IAP Revenue") and when clients purchase the digital advertising inventory of the Company's portfolio of Apps ("IAA Revenue").

The CODM evaluates the performance of each operating segment using revenue and segment adjusted EBITDA. The Company defines segment adjusted EBITDA as revenue less expenses, excluding depreciation and amortization and certain items that the Company does not believe are reflective of the operating segments’ core operations. Expenses include indirect costs that are allocated to operating segments based on a reasonable allocation methodology, which are generally related to sales and marketing activities and general and administrative overhead. Revenue and expenses exclude transactions between the Company's operating segments. The CODM does not evaluate operating segments using asset information.

The following table provides information about the Company's reportable segments and a reconciliation of the total segment adjusted EBITDA to consolidated income (loss) before income taxes (in thousands). For comparative purposes, amounts in prior periods have been recast:

	As of December 31,		
	2022	2021	2020
Revenue:			
Software Platform	$ 1,049,167	$ 673,952	$ 207,285
Apps	1,767,891	2,119,152	1,243,801
Total Revenue	$ 2,817,058	$ 2,793,104	$ 1,451,086
Segment Adjusted EBITDA:			
Software Platform	$ 808,415	$ 457,302	$ 121,114
Apps	254,795	269,512	224,381
Total Segment Adjusted EBITDA	$ 1,063,210	$ 726,814	$ 345,495