Do Investors Understand the Digital Economy? Mobile Apps, Firm Disclosure, and Stock Returns*

Shuping Chen, Yukun Liu, and Xi Wu

December 31, 2024

Abstract

Digital enterprises have fundamentally transformed the global economy. Many new technologies fueling the digital economy were non-existent a decade ago, and our understanding of the implications of these technologies for firm performance is limited. One such new technology is Mobile Apps, iOS or Android apps downloadable onto smartphones and tablets. We find that Mobile App downloads strongly predict next quarters' earnings above and beyond current quarter earnings, firm size, BM ratio, R&D, CAPX, and SG&A. However, the investment community does not fully understand the valuation implications of mobile apps, resulting in predictable analyst forecast errors and predictable excess returns. A long-short strategy on abnormal downloads delivers an EW (VW) annualized return of 12% (11%). This lack of understanding appears to reside primarily with apps that do not have directly observable monetizing features. Notably, firm disclosure of mobile app information in SEC filings mitigates the predictability of analyst forecast errors and returns, consistent with firm disclosure highlighting the importance of mobile apps and reducing investors' information processing costs. Our study advances our understanding of an important new technology that add value to the digital economy and the role of disclosure in enhancing such understanding for the investment community.

*We thank comments from Anne Beatty, Andrew Belnap, Thomas Bourveau, Matthew Cedergren, Yongtae Kim, Sterling Huang (discussant), Charles Lee, Siqi Li, John McInnis, Toby Moskowitz, Bin Miao, Darren Roulstone, Steve Stuben,Frank Zhang, Xiao-Jun Zhang, and workshop participants from Santa Clara University, Southern Methodist University, the University of Texas at Austin, and conference participants of the 2024 Haskayne and Fox Accounting Conference. We thank excellent research assistance from Yanting Huang and Summer Zhao. Corresponding author (shuping.chen@mccombs.utexas.edu). All errors are our own.

1 Introduction

Innovations in digital technologies that generate new business models have fundamentally transformed the global economy. A decade ago, only two of the world's most valuable publicly traded companies were digital enterprises (Apple and Microsoft). In 2024, seven of the worlds' top ten are digital enterprises, including Apple, Microsoft, Alphabet, Amazon, Meta, Nvidia, and Taiwan Semi. The rise of this new digital economy is accompanied by an equally astonishing fall in the old economy's market value. As recent as 2015, Exxon Mobile and Wells Fargo, two reliable blue-chip stalwarts for generations, were two to three times more valuable than Amazon. As of December 2024, Amazon is more than three times more valuable than Exxon Mobile and Wells Fargo combined.

The rise of this digital economy brings new challenges in valuing this new economy, as many of these new technologies were largely non-existent a decade ago.[1] In this paper we examine our understanding of one such new technology, mobile apps (or apps in short), iOS or Android apps that can be downloaded onto smartphones and smart tablets. We also study whether firm disclosures can improve the investment community's understanding of the role of mobile apps in creating value in the digital economy. We address two specific research questions: First, do analysts and investors adequately recognize the valuation implications of mobile apps? Second, does firm disclosure about mobile apps help analysts and investors better understand the valuation implication of mobile apps?

Mobile apps can enhance firm value by driving revenue growth, enhancing customer loyalty and retention, optimizing operations, and creating competitive differentiation. Many mobile apps directly generate revenue through observable monetizing features such as requiring recurring subscription fees, in-app purchases or in-app advertisements (e.g., Meta, Twitter, Peloton, TripAd-

[1]Mobile technology is an important component of the digital economy. Deloitte defines the digital economy as follows: "The digital economy is the economic activity that results from billions of everyday online connections among people, businesses, devices, data, and processes. The backbone of the digital economy is hyperconnectivity which means growing interconnectedness of people, organizations, and machines that results from the Internet, mobile technology and the internet of things (IoT)." Source: https://www2.deloitte.com/mt/en/pages/technology/articles/mt-what-is-digital-economy.html.

visor, Facebook). Even without these in-app monetizing features, mobile apps can still generate value as the primary platform of product delivery (e.g., Uber, Netflix, Spotify, gaming and dating apps) or an alternative platform of product delivery (e.g., Kroger app). Second, many mobile apps offer loyalty programs and deliver personalized experiences and recommendations, both of which can incentivize repeat purchases and improve customer retention, contributing to sustained growth. Third, mobile apps automate many processes, such as order processing, customer support, and account management. This reduces the need for human intervention, saving labor costs and improving operational efficiency. Equally importantly, mobile apps can track customer behavior, such as purchase history and browsing habit. This real-time data provides actionable insights into user needs and preferences, which can be used to optimize offerings, personalize marketing campaigns, and improve product development. Recent research shows that data collected via mobile apps enhance customer retention (Stocchi et al. (2022); Wu (2023)), improve firms' revenue forecasts and results in greater investment efficiencies (Ferracuti et al. (2024)). Last and but not least, mobile apps can increase firms' competitive edge by introducing new revenue models such as recurring subscriptions, and by enabling quicker go-to-market strategies. For example, apps can facilitate faster product launches or allow businesses to test new ideas before a full-scale roll out.

Despite the increasing adoption of mobile apps by firms and the ubiquitous presence of mobile apps in our daily lives, the literature on the investment community's collective understanding of the valuation implications of mobile apps is thin. We tackle this lack of understanding by focusing on mobile apps adopted by U.S. public companies. To address our research questions, we use mobile app downloads, a key app usage attribute tracked by industry specialists as a leading indicator of growth, as our main measure of mobile app value.[2] While firms develop algorithms internally to track app user engagement as a key metric in performance measurement, such internal data are not available to external users. We thus approximate app usage via app download data.

We obtain user download data and app feature data from Sensor Tower, a leading global mobile app data provider. Sensor Tower offers data on millions of mobile apps from more than 100 coun-

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

tries. We first collect all app-level data from Sensor Tower, and collapse the app-level data at the firm-quarter level. In this paper, we focus on mobile apps owned by U.S. public companies from 2012 to 2023.[3] Our sample consists of 831 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, according to data from Sensor Tower, suggesting that our sample firms are important in the global mobile economy.

We first validate mobile app downloads as a measure of mobile app value by establishing the predicative ability of mobile app downloads for next quarter's earnings. Our baseline result shows that quarterly app downloads significantly and positively predict subsequent quarter's earnings. This predictive power is robust to the inclusion of firm size, current quarter 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. This baseline result establishes that on average mobile app downloads have information content for firms' future cash flows.

While it is straightforward to infer that mobile apps have valuation implications for firms with apps that have direct in-app monetizing features such as requiring continuing subscription fees, offering in-app purchase options and placing in-app advertisements, and despite the various indirect channels that mobile apps can enhance value creation as discussed above, skeptics might question mobile apps' ability to generate value for traditional brick-and-mortar companies such as McDonald's and Walmart. We thus split our sample based on whether apps have monetizing features (i.e., subscription model, in-app purchase/ad placement) and re-estimate the earnings prediction model for the two resulting subsamples. We find that app downloads significantly predict

[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.

future earnings for both sets of firms. Thus, app downloads contain information content for firms' future performance across a broad set of firms, for both firms owning apps that have directly observable monetizing features and firms owning apps that do not. The finding is important, because the majority of our sample firms own apps that do not have direct monetizing features.

Turning to our specific research questions, we first examine if analysts incorporate the value created by mobile apps in their earnings forecasts. Following Lee et al. (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 the same set of control variables in the earnings prediction regressions. We find that lagged app downloads significantly predict future SUEs. This result is consistent with analysts not fully incorporating the valuation implication of mobile apps in their earnings forecasts.

Given that analysts are sophisticated information intermediaries, it seems unlikely that they would fail to consider the value created by mobile apps for all app firms, especially if apps have directly observable monetizing features. We thus re-estimate the SUE prediction regressions on the two subsamples split based on whether apps have direct monetizing features. The coefficients on lagged app downloads are only significant in the subsample where apps do not have direct monetizing features, suggesting that analysts fail to incorporate the value created by apps when apps' earnings generation function is not directly observable. However, coefficient differences between the two subsamples are insignificant.

To examine investors' consideration of mobile apps in their investment decisions, 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 firms' 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 return of 99 (93) basis points per month, which translates into annualized abnormal returns of 12% and 11%, respectively, suggesting that investors are leaving substantial money on the table. The portfolio's alphas remain significantly positive after controlling for 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. We further mitigate the possibility that app downloads' predictive ability for future returns is due to unobservable risk factors by documenting a spike in the return reaction around subsequent earnings announcement to lagged abnormal downloads (Bernard and Thomas (1989); Lee et al. (2019); Engelberg et al. (2018)). A risk explanation would have led to returns that accrue evenly over time, not a spike around subsequent earnings announcement.

We conduct a similar cross-sectional analysis on return predictability by splitting our sample based on whether the apps have directly observable monetizing features. We find that the predictive ability of abnormal downloads for future returns resides only in firms with apps that do not have direct monetizing features, and the differences in the hedge portfolio returns and alphas are statistically significant at 5% level or better. Thus, investors behave similarly as analysts: they do not appear to properly incorporate the value of mobile apps when apps do not have observable monetizing features. The above analyses on analysts and investors combined is consistent with an information processing cost explanation: analysts and investors appear to consider only the subset of information that is readily available and observable due to the limits to their information processing capacity.

Given the above findings, a natural next step in our investigation is to examine if firm disclosure in their SEC filings, the one source of information that is easily obtainable and observable to all investors, could reduce investors' information processing costs, thus in turn reducing analysts' forecast errors and mitigate the bias in investors' expectations. This investigation is motived by prior research that shows that investors use existing financial disclosures to facilitate investment decisions (Drake et al. (2016); Bourveau and Schoenfeld (2017); Blankespoor et al. (2020)). We construct a firm disclosure measure using the average word mentions of mobile app information across the top three regulatory filings – firms' 10-K, 10-Q, and 8-K reports. As this measure only counts related words and phrases, it likely captures a lower bound of firms' app-related disclosure, as some firms (such as Bumble and AppLovin) also tabulate detailed quantitative information such as the revenue generated per user in their SEC filings. However, we note that this should not affect our inference as long as firms' total disclosure on mobile apps is positively related to our word count measure, as we only rely on this measure to identify cross-sectional differences.

We repeat the SUE predictability and future return predictability analysis by splitting our sample based on the sample median of the firm disclosure measure. 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 above sample-median disclosure. Taken together, this set of results suggests that firm disclosure enables the investment community to better understand the importance of mobile apps to firm performance.

Accounting research on mobile apps' role in the digital economy is scarce. To the best of our knowledge, we are aware of only three other papers: Wu (2023), Ferracuti et al. (2024), and Kim and Wu (2024). Wu (2023) derives a mobile app-value measure from the market reaction to app releases and shows that this app value measure can predict lower firm risk and higher future growth. Ferracuti et al. (2024) find that after app adoption, management revenue guidance is more accurate, and firms appear to mitigate both over- and under-investment in key assets. Kim and Wu (2024) find that insider trading profits are higher after firms adopt mobile apps. Our paper complements these papers in bringing greater awareness of mobile apps as an important technology that adds value to the digital economy. We also advance this research by further delving into the role of firm disclosure in facilitating our collective understanding of mobile apps' importance to the digital economy.

Our research is distinctly different from an early literature on the value relevance of web traffic for internet firms in both motivation and conclusion (e.g., Trueman et al. (2000); Trueman et al. (2001); Rajgopal et al. (2003)). This early literature searches for metrics that can explain the high market valuation of emerging internet firms when earnings cannot, and generally concludes that investors and analysts are rational in relying on web traffic to price internet stocks. Our motivation is to highlight an under-studied digital technology that can create value for firms, yet whose valuation implications are not fully understood by the investment community due to investors' limits to information processing capacity. Our examination of the role of firm disclosure in assisting analysts and investors further sets our paper apart from this early literature, which does not examine firm disclosure or investors' information processing costs at all.

Our research is also different from research using alternative data to predict earnings and constrain manager behavior (e.g., Givoly et al. (2019); Dichev and Qian (2022); Chiu et al. (2023); Zhu (2019); Blankespoor et al. (2022)). The key difference between mobile apps and these other indicators is that mobile apps create new business models that help generate earnings and significantly change consumer behavior in a sweeping manner, whereas the other indicators and alternative data examined in prior literature reflects performance, but do not generate future economic benefits.

Our finding that firm disclosure helps analysts and investors should provide useful food for thought for the SEC in its deliberation of disclosure standards. The SEC's disclosure mandate is constantly expanding, focusing not only on financial performance, but a host of other issues. 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.[4] 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. Importantly, information about performances in the digital economy, such as mobile app data, is rarely available to the public. 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.[5]

[4]For example, see Christensen et al. (2017), Bourveau et al. (2022), and Baik et al. (2024) for recent evidence.

[5]According to the U.S. Bureau of Economic Analysis, in 2022, digital economy value added account for 10% of U.S. GDP, and digital economy real value added grew by 6.3% whereas the total U.S. real GDP growth is 1.9%.

2 Background and Related Literature

2.1 Mobile Apps

Mobile apps, iOS and Android apps that can be downloaded onto smartphones and smart tablets, have upended commerce by transforming how business generate earnings and how consumers access products and services. 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 $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 both in consumer-facing industries such as grocery chains and restaurants, and in less obvious industries such as healthcare and banking. The Wall Street Journal also notes that big companies in the Fortune 100 are playing catch-up in investing in mobile apps.[6]

Mobile apps offer the convenience of consumption on the go: users can access information and services, consume digital content, 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 and accelerate earnings generation. 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 without ever setting foot in the actual store, which saves not only the cost of gas but also the time to drive in traffic and find parking. App.ai, a leading app intelligence firm, reports that consumers in 13 countries, including the U.S. and U.K, are now spending an average of four to five hours per day on mobile apps.

Some app firms, such as Uber and Match Group Inc. (which owns Tinder, OkCupid, and

[6]"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; "WhatsAppâs Business User Base Grew Tenfold from 2019," The Wall Street Journal, July 9, 2020; https://www.forbes.com/advisor/banking/banking-trends-and-statistics/, https://deloitte.wsj.com/cio/fortune-100-playing-catch-up-with-mobile-01671218440.

other dating apps), rely predominantly on mobile apps to generate earnings. Mobile apps can also generate earnings directly through continuing subscription fees to access content (e.g., fitness apps such as Peloton), in-app purchase options (e.g., most game apps, language-learning apps such as Duolingo, digital music streaming app Spotify), and in-app ad placements (e.g., Duolingo, Spotify, Facebook). Equally importantly but less observable, mobile apps also generate value for firms by leveraging the real-time consumer data collected by apps to improve their products and enhance user engagement and retention. Many consumer facing mobile apps, for example grocery store apps, also contain gamification components and/or loyalty programs to incentivize user engagement. For example, grocery store apps such as Kroger and HEB deliver coupons and offers directly to users' mobile devices, increasing users' engagement and adding value to their shopping experience.

As an example of the importance of mobile apps to firms, Meta Platforms Inc. consistently tracks key engagement metrics like daily active users, monthly active users, and time spent on apps. In their recent quarterly earnings calls CEO Mark Zuckerberg highlighted the company's focus on using AI to better improve user experience and enhance user retention. In their 10-K filings Meta also prominently discusses user engagement across its "family of apps" which includes Facebook, Instagram, WhatsApp, and Messenger. Other app firms such as Bumble (dating app firm) and AppLovin (gaming app firm) discuss attracting new app users, mobile app user retention and engagement as important risk factors in Item 1A of their 10-Ks. In sum, mobile apps provide valuable data-driven insights for businesses to make timely decisions to enhance their products and services, which further accelerates earnings 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 some firms include discussions of mobile apps in their regulatory filings, the literature on firms' use of mobile apps is thin. 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 whose apps 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 are more accurate, and firms exhibit less underinvestment in capital assets and less overinvestment in inventory. While the above two papers focus on the benefits of having mobile apps, Kim and Wu (2024) study the potential costs of firms owning apps by examining the abnormal insider trading gains after app adoption. Our paper examines whether mobile apps can generate earnings for firms, and the relation between app disclosure in firms' regulatory filings and investor valuation.

Our paper is distinctly different from an early literature on the value-relevance of non-financial information in internet companies (Trueman et al. (2000); Trueman et al. (2001); Rajgopal et al. (2003)) in both motivation and inferences. This early literature seeks to identify metrics that can explain the high valuation for a small sample of emerging internet firms (around 90 firms) using data spanning seven quarters. This literature find no excess returns in their portfolio tests, and conclude that investors and analysts appear to be rational in using web traffic information to value firms. This early literature also finds no evidence that web traffic predicts future firm performance. In contrast, we find that lagged mobile apps downloads, a measure capturing growth, predict future earnings, and that analysts and investors do not fully incorporate the value of mobile apps in their earnings forecasts and investment decisions. Importantly, we also show that firm disclosure mitigates analyst forecast errors and excess returns, an investigation absents from this early literature. Our sample also spans a much broader set of the U.S. economy and we also use a much longer sampling period of 12 years.

Our paper is related to, but different from, a broader literature documenting the usefulness of alternative data in predicting performance and detecting earnings management. For example, Givoly et al. (2019) show that indicators such as passenger load factors for airlines have incremental information content for stock prices over earnings. Dichev and Qian (2022) construct a measure of aggregated consumer purchases for 311 firms in the packaged-goods industry using NielsenIQ Scanner data, and find that this measure can predict 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 real-time credit card purchases and satellite images to examine the interaction between these data and managerial behavior (Blankespoor et al. (2022); Zhu (2019)). However, unlike mobile apps, these alternative data sources, while reflecting performance, do not lead to the creation of new business models or changed consumer behavior.

3 Data and Sample

3.1 Data

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 2023. 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 in the sample of public firms.

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 2023, 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 growth measure. We also collect information on the 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.[7]

We obtain firms' quarterly financial data from Compustat, stock price data from CRSP, and analyst forecast data from I/B/E/S. 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. The main sample contains 831 unique U.S. public companies.

3.2 Descriptive Statistics

Figure 1 presents graphical evidence of the increasing trend of app downloads worldwide (Panel A) and in our sample (Panel B) over the 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. Although our sample of firms constitutes a small fraction 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.

We present descriptive statistics on app downloads and key variables in Table 1. In Panel A of

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

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 831 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 dominates mobile app ownership, accounting for 34% of the 831 sample app firms. In contrast, 18% of the firms in the Compustat universe are high-tech 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 our sample. This percentage is more than two times higher than the 10% of consumer-facing firms in the Compustat universe.

In Panel B of Table 1 we provide a descriptive comparison of the key firm characteristics between Compustat firms and our app sample. App firms are on average older, bigger in size, and have higher growth than the Compustat universe. Interestingly, the descriptive statistics also show that app firms have less R&D and capital investments.

Table 2 of Panel A presents the distribution of key variables used in our tests. Appendix A presents detailed definitions 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 3,226 thousand and a median of 42 thousand. The firm disclosure measure Dis is also highly right skewed with a mean word count of 16.4 per filing and a median word count of 2.2 per filing. The app monetizing indicator variable $1_{monetize}$ shows that 19% of our sample observations are firms with apps that have the above two direct monetizing features. 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 ($log(Dis+1)$) without scaling by total assets as this is already a scaled measure (app-related word count averaged across three top regulatory filings).

Panel B of Table 2 presents the correlation matrix for the main test variables. Correlation coefficients with one asterisk are statistically significant at the 5% level. Not surprisingly, all the app related measures, app downloads, the monetizing indicator, and the firm disclosure measure are all positively correlated with one another.

3.3 Validating mobile app downloads as an app value measure

We validate mobile app downloads as a measure of app value by regression quarter q earnings on quarter $q-1$ $log(DL/AT)$, and we control for 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. We include firm and time fixed effects to control for time-invariant firm characteristics and common shocks at a given time, and cluster standard errors at the firm level.

The results are summarized in Table 3. Panel A of Table 3 presents the baseline results. Controlling for firm size (Column 1) and current earnings (Column 2), mobile app downloads ($log(DL/AT)$) positively and significantly predict 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 app downloads is associated with an increase of close to \$10 million (2.7% of the sample mean) in 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 1% level.[8]

We tabulate the results in Panel B of Table 3 for the two subsamples split on the app monetizing indicator variable $1_{monetize}$. For parsimony of presentation we omit the tabulation on control variables. The coefficients on log(DL/AT) are statistically significant in both subsamples. This finding is important because our analysis below shows that the investment community's lack of understanding of the valuation implication of mobile apps is concentrated in firms that have mobile

[8]In Table 8 tabulated in Appendix B we also find that lagged app downloads predict future revenue. Table 9 of Appendix B further examines if existing balance sheet intangible asset accounts subsume the ability of mobile app downloads to predict future earnings. None of the coefficients on the additional control variables intangible assets $(INTAN/AT)_{q-1}$ and their components such as capitalized software development costs $(SFT/AT)_{q-1}$, goodwill $(GW/AT)_{q-1}$, and other intangible assets $(INTANO/AT)_{q-1}$ is significant. Even though the coefficient on the total Q measure (Q^{tot}) from Peters and Taylor (2017), which includes information of both R&D and capital investments, is significant, notice that the point estimates of mobile app downloads remain positive and statistically significant, and the coefficients of 0.15 and 0.16 are stable after the inclusion of (Q^{tot}) and are similar to those obtained from Panel A of Table 3.

apps without direct monetizing features. The point estimate of app downloads for future earnings is larger for apps with monetizing features (point estimates of 0.40 in Column (4) versus 0.10 in Column (2)), though the differences across the two subsamples are insignificant (p-value of 0.131).

4 Empirical Tests and Results

4.1 Do Analysts and Investors Fully Recognize the Valuation Implications of Mobile Apps?

4.1.1 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 Panel A of 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 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. From Column (1) to Column (6) we sequentially include more control variables. Column (6) shows that the coefficient estimate on mobile app downloads, with all control variables included, is positive at 5.70 and statistically significant at the 5% level.

In Panel B of Table 4 we tabulate the SUE prediction regressions subsampled by whether apps have direct monetizing features based on the indicator variable $1_{monetize}$. The results show that lagged app downloads' predictive ability for analyst forecast error is concentrated in apps without direct monetizing features. The coefficients on $log(DL/AT)$ are insignificant in the subsample of apps with direct monetizing features. Though the differences in the coefficient estimates between the two subsamples are not statistically significant, they are large in economic magnitude.

4.1.2 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 5. Panel A of Table 5 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 99 (93) basis points, which translates into a non-trivial annualized excess return of 12% (11%) per year.

Panel B of Table 5 reports the regression results on the portfolio alphas and factor loadings of the hedged long-short portfolios using the CAPM, the Fama-French 3-factor (Fama and French (1993)), 5-factor (Fama and French (2015)), and the Fama-French 5-factor plus momentum factor

(Fama and French (2015); Carhart (1997)) 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.[9] [10]

Similar to our analysis on the cross-sectional differences in analysts' understanding of mobile apps' value, we repeat the same analysis above on the two subsamples split on the app monetizing indicator $1_{monetize}$. Panel C of Table 5 presents the hedged portfolio returns and portfolio alphas across the two subsamples. We find that the hedge portfolio returns and alphas are only significant for firms with apps that do not have direct monetizing features. The differences in mean hedged portfolio returns and alphas across the two subsamples are significant at the 5% level. Thus, investors appear to behave similarly as analysts: they are able to price stocks correctly when apps' earnings-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 earnings is not directly available.

[9]For robustness, we estimate Fama-MacBeth regressions of month returns on lagged abnormal downloads and control for firm size, book-to-market, gross profit, capital investment, debt and accruals. The results remain similar.

[10]To further mitigate the concern that our return results are driven by unexplained risks, we follow a long time of literature and examine whether there is a spike in price reaction to lagged abnormal returns during the subsequent quarterâs earnings announcement (Bernard and Thomas (1989); Engelberg et al. (2018); Lee et al. (2019)). A risk explanation would lead to returns more evenly accrued over subsequent periods. We thus regress daily stock returns surrounding a 7-day earnings announcement window on lagged abnormal downloads. The results are presented in Table 10 in Appendix B. The coefficient from the earnings announcement window return is 0.176. In contrast, the coefficient from a baseline regression of daily stock returns on lagged abnormal downloads is 0.025. The spike during the earnings announcement window is hard to square with a risk explanation.

4.2 Firm Disclosure and Mobile App Recognition

4.2.1 Measure of Firm Disclosure of Mobile Apps in Regulatory Filings

In the previous section, we find that both analysts and investors fail to fully appreciate mobile apps' importance for app firms with apps that do not have observable monetizing features, leading to predictable forecast errors and predictable stock returns. In this section, we examine whether firm disclosure of mobile app information in their SEC filings helps analysts and investors better understand the value of mobile apps and mitigate predictable forecast errors and stock returns.

We focus on firm disclosure for two reasons. First, a long-standing literature has established that investors use information contained in firms' SEC filings to facilitate investment decisions (Drake et al. (2016); Bourveau and Schoenfeld (2017); Blankespoor et al. (2020)). Second, firm disclosure is immediately available to the investing public upon filing with the SEC, and is the least costly type of public information for investors to acquire. In other words, firm disclosure imposes minimum information processing costs on investors. While analysts and investors indeed can also obtain app-related information from data providers such as Sensor Tower, they still face non-trivial information processing costs of having to aggregate individual app information to the firm level. In comparison, firm disclosure is the most direct information investors can obtain.

We measure firm disclosure of mobile app information by counting relevant words or phrases ("mobile application", "app", "in-app", "download", "user", "iOS", and "android") in 10-Ks, 10-Qs, and 8-Ks. Our resulting mobile app disclosure measure, Dis, is the average mentions of app information across the top three regulatory filings for a given firm in a given year.

Appendix C provides some excerpts of various disclosures included in Bumble and AppLovin's 2022 10-Ks. These excerpts of 10-Ks all discuss app 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 users and revenue generated per app user. Thus, our disclosure measure *Dis* likely captures the lower bound of the amount of 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 the association between firm disclosure and firm characteristics. The key firm characteristics we examine include whether firms' apps have direct monetizing features and firm concerns about proprietary costs. Firms trade off the benefits of disclosure against the costs of disclosure. It is possible that firms with apps with direct monetizing features have greater proprietary cost concerns, resulting in a lower likelihood that they will disclose app related information in their SEC filings (Jovanovic (1982); Verrecchia (1983)). 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)). We note that unlike major customers of a firm that generate significant revenues, users of mobile apps are atomistic, and revealing revenue generated by each user is less likely to hurt a firm's competitive edge. To the extent firms view mobile app-related information as non-proprietary, we may also observe more disclosure from firms whose apps have direct monetizing features.

We present our determinant analysis in Table 6. Panel A presents the regression of $log(Dis+1)$ on the indicator variable $1_{monetize}$, and firm-level measures of proprietary cost concerns using the trade secret measure from Glaeser (2018) ($TrdSecret$), and firms' markup ($Markup$). In addition, we also include industry competition measures using 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 regressions in Table 3. In Column (3) we further include the industry dummies for manufacturing, high-tech, healthcare, and other industries, and thus the baseline industry is the consumer industry.

Panel A of Table 6 shows that, ceteris paribus, firms disclose more app-related information in their SEC filings the more direct mobile apps are to their profits: the coefficients on the indicator variable $1_{monetize}$ are significantly positive at the 1% level across all three model specifications. We also find significantly positive coefficients on the proxy for proprietary information ($TrdSecret$), on industry price cost margin PCM, and on the proxy capturing R&D expenditures (RD/AT). It is possible that firms that rely more on mobile apps to generate revenue engage in more innovative R&D activities, resulting in more trade secrets that need to be protected from competitors.

In Panel B of Table 6 we examine if app downloads' predicative ability for future earnings varies with firm disclosure. We re-estimate the earnings predictability regression subsampled by median firm disclosure. We find that app downloads predict future earnings regardless of firm disclosure. Thus, the under-recognition of mobile apps as a value driver we have documented so far is more likely due to information awareness – that analysts and investors are less aware that mobile apps generate value for all firms, not just for a subset of firms where apps have observable monetizing features.

4.2.2 SUE and Return Predictability Subsampled by Firm Disclosure

If information awareness is an issue, then greater firm disclosure of relevant information can conceivably bring greater awareness to mobile apps as a value driver. To examine whether firm disclosure helps analysts and investors better incorporate mobile app information in their earnings forecasts and investment decisions, we partition our sample based on the firm disclosure measure $log(Dis+1)$. We then re-estimate the SUE prediction regression subsampled by median firm disclosure, and re-estimate the hedge portfolio returns and alphas subsampled by median firm disclosure.

Table 7 presents the results. Panel A presents the results on the SUE prediction regression. Given our finding in Table 6 that firms with apps that have in-app monetizing features also provide more disclosure, we further include the monetizing indicator $1_{monetize}$ as an additional control variable in our SUE prediction regressions. The results show that the predictability of lagged app downloads for future SUEs disappears from the subsample with above sample-median firm disclosure, as the coefficients on lagged downloads in Columns (3) and (4) are not significant. In contrast, the predictability remains for the below sample-median subsample, with coefficients in Columns (1) and (2) significant at the 1% level, respectively. Test of coefficient differences between the two subsamples are significant at the 5% and 10% level with and without additional controls, respectively. This set of results is largely consistent with analysts better able to incorporate the value created by mobile apps into their earnings forecasts when there is more firm disclosed information on mobile apps.

Panel B presents the return estimation results. 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. Similar to what we find in Panel A, lagged abnormal downloads can only predict returns in the subsample of firms with below-median firm disclosure. The average hedged long-short strategy return for the below median subsample is 1.43% per month while that of the above median subsample is only 0.45% 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 1.31% per month, while it is only 0.56% for the above median subsample. Test of differences between the subsamples are significant at 1% level for hedged portfolio returns and at 10% level for alphas. These results suggest that firm disclosure helps investors better incorporate information about mobile apps in valuing the stocks, leading to smaller predictable returns.

5 Conclusion

Mobile apps are becoming an integral part of our daily lives and are increasingly being adopted by firms to enhance their profits. Mobile apps create value for firms either directly through in-app monetizing features such as requiring subscription fees, in-app purchase options, and in-app ad placements, or indirectly through better customer engagement or product improvement using the data gathered by mobile apps. 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 as a growth indicator, and some firms themselves discuss the importance of mobile app usage in their annual reports.

As mobile apps were largely non-existent over a decade ago, our understanding of the valuation implication of mobile apps for the digital economy is limited. We study whether the investment community at large adequately understands the valuation implication of mobile apps for U.S. public companies, and whether firm disclosure of mobile app related information in their SEC filings can help analysts and investors better understand the valuation implications of mobile apps. We use user downloads from Sensor Tower, a provider of world-wide mobile app usage data, as a measure of app value, and examine whether app downloads can systematically predict analyst forecast errors and stock returns.

We first validate our mobile app value measure by demonstrating 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 with apps that have direct monetizing features, but also for other more traditional firms that adopt mobile apps with no direct monetizing features, but use apps as an alternative means to deliver products (e.g., McDonald's, Walmart).

Turning to our research questions, we first document that lagged mobile app downloads significantly predict subsequent analyst forecast errors, and that lagged abnormal app 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 in firms owning apps that do not observable direct monetizing features. This set of results is consistent with an information processing cost explanation: Since attention is a scarce limited resource, analysts and investors may only consider a subset of information that is readily available. Second, 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. The second set of results is consistent with firm disclosure highlighting the importance of mobile apps to their operations, reducing investors' information processing costs, and enhancing the understanding of the investment community as a whole.

Our findings have important implications for researchers, regulators, and the investment community in general. We hope our study, together with the few existing studies, will generate more research interest in new digital technologies that contribute to growth of the digital economy.

References

Baik B, Even-Tov O, Han R, Park D. 2024. The real effects of conflict minerals disclosures. *Journal of Accounting Research* **62**: 551–587.

Bernard VL, Thomas JK. 1989. Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting research* **27**: 1–36.

Blankespoor E, deHaan E, Marinovic I. 2020. Disclosure processing costs, investorsâ information choice, and equity market outcomes: A review. *Journal of Accounting and Economics* **70**: 101344.

Blankespoor E, Hendricks BE, Piotroski J, Synn C. 2022. Real-time revenue and firm disclosure. *Review of Accounting Studies* **27**: 1079–1116.

Bourveau T, Chowdhury M, Le A, Rouen E. 2022. Human capital disclosures. *Available at SSRN 4138543* .

Bourveau T, Schoenfeld J. 2017. Shareholder activism and voluntary disclosure. *Review of Accounting Studies* **22**: 1307–1339.

Carhart MM. 1997. On persistence in mutual fund performance. *The Journal of Finance* **52**: 57–82.

Chiu PC, Teoh SH, Zhang Y, Huang X. 2023. Using google searches of firm products to detect revenue management. *Accounting, Organizations and Society* **109**: 101457.

Christensen HB, Floyd E, Liu LY, Maffett M. 2017. The real effects of mandated information on social responsibility in financial reports: Evidence from mine-safety records. *Journal of Accounting and Economics* **64**: 284–304.

Dichev ID, Qian J. 2022. The benefits of transaction-level data: The case of nielseniq scanner data. *Journal of Accounting and Economics* **74**: 101495.

Drake MS, Roulstone DT, Thornock JR. 2016. The usefulness of historical accounting reports. *Journal of Accounting and Economics* **61**: 448–464.

Engelberg J, McLean RD, Pontiff J. 2018. Anomalies and news. *The Journal of Finance* **73**: 1971–2001.

Fama EF, French KR. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* **33**: 3–56.

Fama EF, French KR. 2015. A five-factor asset pricing model. *Journal of Financial Economics* **116**: 1–22.

Ferracuti E, Koo M, Lee M, Stubben S. 2024. Acquisition of customer information and corporate decision making. *Available at SSRN 4682350* .

Givoly D, Li Y, Lourie B, Nekrasov A. 2019. Key performance indicators as supplements to earnings: Incremental informativeness, demand factors, measurement issues, and properties of their forecasts. *Review of Accounting Studies* **24**: 1147–1183.

Glaeser S. 2018. The effects of proprietary information on corporate disclosure and transparency: Evidence from trade secrets. *Journal of Accounting and Economics* **66**: 163–193.

Jovanovic B. 1982. Truthful disclosure of information. *The Bell Journal of Economics* : 36–44.

Kim S, Wu X. 2024. The dark side of digital transformation: The case of mobile app and insider gains. *Working Paper* .

Lee CM, Sun ST, Wang R, Zhang R. 2019. Technological links and predictable returns. *Journal of Financial Economics* **132**: 76–96.

Rajgopal S, Venkatachalam M, Kotha S. 2003. The value relevance of network advantages: The case of e–commerce firms. *Journal of Accounting Research* **41**: 135–162.

Stocchi L, Pourazad N, Michaelidou N, Tanusondjaja A, Harrigan P. 2022. Marketing research on mobile apps: past, present and future. *Journal of the Academy of Marketing Science* : 1–31.

Trueman B, Wong MF, Zhang XJ. 2000. The eyeballs have it: Searching for the value in internet stocks. *Journal of Accounting Research* : 137–162.

Trueman B, Wong MF, Zhang XJ. 2001. Back to basics: Forecasting the revenues of internet firms. *Review of Accounting Studies* **6**: 305–329.

Verrecchia RE. 1983. Discretionary disclosure. *Journal of Accounting and Economics* **5**: 179–194.

Wu X. 2023. Mobile app, firm risk, and growth. *Firm Risk, and Growth (March 15, 2023)* .

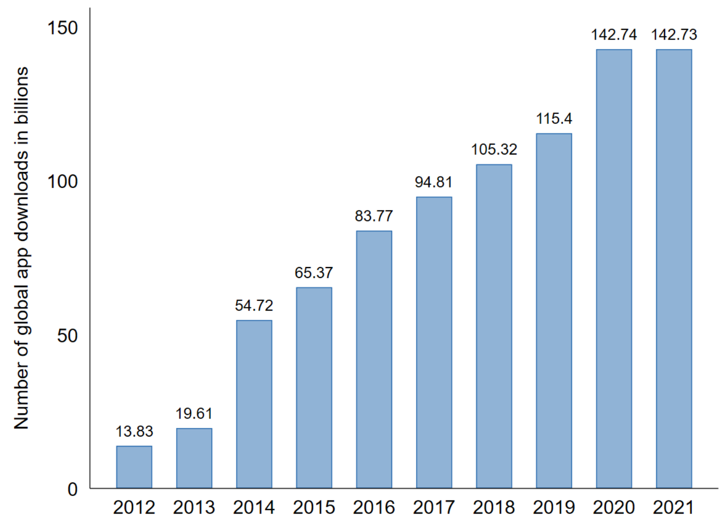
Zhu C. 2019. Big data as a governance mechanism. *The Review of Financial Studies* **32**: 2021–2061.

Table & Graphs

Figure 1: Mobile Apps 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) Total Number of World Wide Downloads



(b) Downloads in Sample

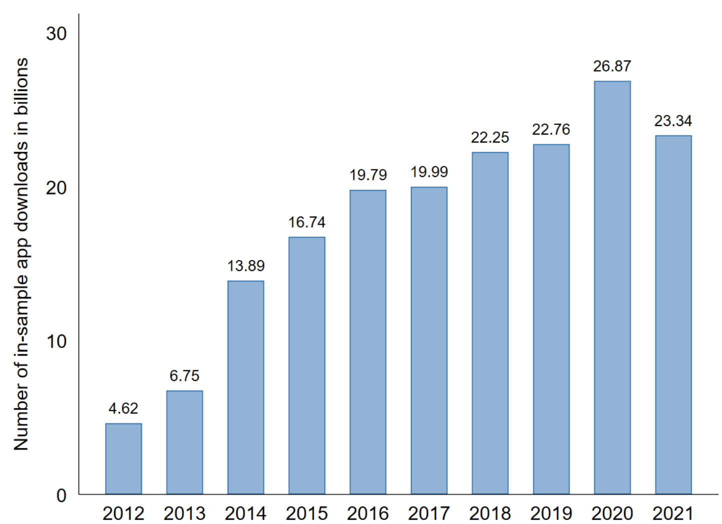


Table 1: Sample Comparison

This table reports the summary statistics of the sample used in this paper in contrast to the Compustat universe of firms in the same sampling period of 2012-2023. Panel A compares the sample composition used in the paper and the full Compustat universe for each of the Fama-French 5 industry. Panel B compares the firm characteristics of the Compustat sample and the app sample. * 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	210	25.27	25.27	210/956=0.22
Manufacturing	2	1,055	11.39	21.71	2	103	12.39	37.67	0.10
High Tech	3	1,664	17.96	39.67	3	278	33.45	71.12	0.17
Health	4	1,573	16.98	56.64	4	48	5.78	76.90	0.03
Other	5	4,017	43.36	100	5	192	23.10	100	0.05
Total	Total	9,265	100		Total	831	100		0.09

Panel B	Compustat sample		App sample		Diff
	Mean	SD	Mean	SD	
Firm age	15.17	12.50	24.23	16.25	9.05*
$\log(AT)$	6.12	2.12	8.65	1.82	2.53*
BM	0.73	0.69	0.41	0.37	-0.32*
RD/AT (%)	1.55	3.43	0.94	1.75	-0.61*
CAPX/AT (%)	1.03	1.58	0.95	1.06	-0.07*
SGA/AT	7.25	7.57	7.32	6.47	0.07

Table 2: Summary Statistics

Panel A reports the mean, standard deviation, and distribution of the main variables used in the paper. Panel B reports the correlation matrix for the main test variable. * indicates significance at the 5% level.

Panel A	Mean	SD	25%	50%	75%
DL (in thousands)	3226.51	15732.47	1.52	46.22	427.39
$\log(DL/AT)$	2.58	2.64	0.17	1.76	4.40
$\log(DL/AT)^{ab}$	0.02	0.44	-0.15	-0.00	0.16
$1_{monetize}$	0.19	0.39	0	0	0
dis	16.41	37.28	1.06	2.22	7.54
$\log(dis+1)$	1.66	1.33	0.72	1.17	2.14
NI/AT (%)	0.78	3.37	0.19	1.12	2.24
AT (in mils)	51718	194191	1702	5819	22929
$\log(AT)$	8.76	2.00	7.44	8.67	10.04
BM	0.40	0.35	0.15	0.30	0.54
RD/AT (%)	1.00	1.80	0.00	0.00	1.36
CAPX/AT (%)	0.95	0.97	0.30	0.65	1.28
SUE ($\times$100)	77.57	130.61	3.09	63.66	145.22

Panel C	$\log(DL/AT)$	$\log(DL/AT)^{ab}$	$1_{monetize}$	$\log(dis+1)$	NI/AT	$\log(AT)$	BM	RD/AT	CAPX/AT	SUE
$\log(DL/AT)$	1									
$\log(DL/AT)^{ab}$	0.080*	1								
$1_{monetize}$	0.501*	-0.079*	1							
$\log(dis+1)$	0.239*	-0.089*	0.203*	1						
NI/AT (%)	-0.162*	0.099*	-0.011	-0.074*	1					
$\log(AT)$	-0.335*	-0.004	0.014	-0.126*	0.221*	1				
BM	-0.189*	-0.011	-0.049*	-0.041*	-0.142*	0.247*	1			
RD/AT (%)	0.283*	-0.058*	0.135*	0.264*	-0.326*	-0.341*	-0.306*	1		
CAPX/AT (%)	0.114*	0.122*	-0.008	-0.019	0.053*	-0.126*	-0.083*	-0.036*	1	
SUE ($\times$100)	-0.003	-0.005	-0.001	-0.008	0.087*	0.000	-0.125*	0.128*	-0.074*	1

Table 3: Validating Mobile App Downloads Measure

This table reports the regression results of earnings on lagged mobile app downloads. Panel A reports the baseline results. Panel B reports the regression results subsampled by the in-app monetizing feature indicator. Firm and time fixed effects are included. Controls include NI_{q-1}, log(AT), BM, RD/AT, CAPX/AT, and SGA/AT. Standard errors are clustered at the firm level and shown in parentheses. Variable definitions are presented in the Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A	(1)	(2)	(3)
VARIABLES	NI/AT_q	NI/AT_q	NI/AT_q
$\log(DL/AT)_{q-1}$	0.19***	0.16***	0.16***
	(0.06)	(0.05)	(0.06)
NI/AT_{q-1}		0.26***	0.22***
		(0.02)	(0.02)
$\log(AT)_{q-1}$			-0.15
			(0.11)
BM_{q-1}			-1.60***
			(0.14)
RD/AT_{q-1}			-0.09
			(0.06)
$CAPX/AT_{q-1}$			0.13***
			(0.04)
SGA/AT_{q-1}			-0.05**
			(0.02)
Constant	0.43***	0.29**	2.63**
	(0.15)	(0.12)	(1.05)
Firm & Time FEs	Y	Y	Y
Observations	28,134	28,126	19,808
R-squared	0.49	0.52	0.54

Table 3 (continued)

Panel B: Subsample Results				
	$1_{monetize}=0$		$1_{monetize}=1$	
	(1)	(2)	(3)	(4)
VARIABLES	NI/AT_q	NI/AT_q	NI/AT_q	NI/AT_q
$\log(DL/AT)_{q-1}$	0.15**	0.10*	0.40***	0.40**
	(0.06)	(0.06)	(0.13)	(0.19)
Firm & Time FEs	Y	Y	Y	Y
Controls	N	Y	N	Y
Observations	23,730	16,246	5,477	3,558
R-squared	0.53	0.58	0.42	0.50
Coeff diff			(3) - (1)	(4) - (2)
p-value			0.092	0.131

Table 4: Predicting Future SUE

This table reports regression result of SUE (standardized unexpected earnings) on lagged mobile app downloads. Panel A reports the baseline results. Panel B reports regression result of SUE (standardized unexpected earnings) on lagged mobile app downloads, subsampled by the in-app monetizing feature indicator. 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	(1)	(2)	(3)	(4)	(5)	(6)
$\log(DL/AT)_{q-1}$	5.94**	3.94*	5.97***	4.08*	8.72***	5.70**
	(2.42)	(2.37)	(2.15)	(2.09)	(2.55)	(2.49)
SUE_{q-1}			11.37***	10.83***	10.62***	9.86***
			(0.82)	(0.84)	(0.98)	(1.02)
SUE_{q-2}			2.09***	2.49***	2.43**	2.80***
			(0.77)	(0.77)	(0.97)	(0.98)
SUE_{q-3}			1.56**	1.14*	1.75**	1.44*
			(0.68)	(0.69)	(0.80)	(0.81)
SUE_{q-4}			-0.34	-0.16	-0.64	-0.29
			(0.66)	(0.66)	(0.76)	(0.77)
$\log(AT)_{q-1}$					14.76***	4.24
					(5.21)	(6.46)
BM_{q-1}					19.11*	-12.99
					(11.29)	(12.12)
RD/AT_{q-1}					-0.74	-2.75
					(3.37)	(3.58)
$CAPX/AT_{q-1}$					-3.77	-1.26
					(2.48)	(2.57)
SGA/AT_{q-1}					0.45	1.60
					(1.08)	(1.12)
Constant	64.55***	69.33***	53.40***	58.13***	-81.71*	20.37
	(5.80)	(5.67)	(5.28)	(5.11)	(48.37)	(58.41)
Firm FE	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y
Observations	19,528	19,528	18,930	18,930	13,601	13,601
R-squared	0.14	0.17	0.15	0.19	0.16	0.20

Table 4 (continued)

Panel B: Subsample Results				
	$1_{monetize} = 0$		$1_{monetize} = 1$	
	(1)	(2)	(3)	(4)
VARIABLES	SUE_q	SUE_q	SUE_q	SUE_q
$\log(DL/AT)_{q-1}$	5.57**	6.83**	-0.57	-0.52
	(2.27)	(2.51)	(4.81)	(7.91)
Firm & Time FE	Y	Y	Y	Y
Lags	Y	Y	Y	Y
Controls	N	Y	N	Y
Observations	15,557	11,195	3,367	3,403
R-squared	0.20	0.22	0.21	0.23
Coeff diff			(3) - (1)	(4) - (2)
p-value			0.239	0.432

Table 5: 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. 1-10 are the decile portfolio excess returns from the lowest decile to the highest decile. 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 Fama-French 3-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 factor models. Panel C reports the regression results of returns on lagged mobile app downloads, subsampled by the in-app monetizing feature indicator. Variable definitions are presented in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A: Portfolio Sorting

%	EW		VW	
	Mean	Alpha	Mean	Alpha
Low	0.49	-0.47	0.17	-0.70**
	(0.71)	(0.30)	(0.58)	(0.31)
2	0.77	-0.16	0.70	-0.23
	(0.61)	(0.22)	(0.55)	(0.22)
3	0.93	0.04	0.72	-0.14
	(0.57)	(0.17)	(0.50)	(0.19)
4	0.71	-0.21	0.87*	0.05
	(0.60)	(0.17)	(0.50)	(0.22)
5	1.01*	0.08	0.58	-0.25
	(0.60)	(0.18)	(0.49)	(0.17)
6	1.04*	0.19	0.76*	0.09
	(0.55)	(0.19)	(0.44)	(0.24)
7	1.02*	0.16	0.99*	0.12
	(0.54)	(0.16)	(0.51)	(0.19)
8	1.45***	0.61***	1.30***	0.47**
	(0.55)	(0.19)	(0.49)	(0.20)
9	1.43**	0.52**	0.92	0.01
	(0.58)	(0.20)	(0.56)	(0.27)
High	1.48**	0.66*	1.09**	0.23
	(0.67)	(0.34)	(0.52)	(0.26)
H-L	0.99***	1.13***	0.93**	0.93**
	(0.33)	(0.33)	(0.43)	(0.43)

Table 5 (continued)

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	1.11***	1.13***	1.02***	0.96***	0.86**	α	0.97**	0.93**	1.01**	0.71*	0.82*
	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)		(0.44)	(0.43)	(0.43)	(0.41)	(0.42)
MKTRF	-0.15**	-0.15**	-0.09	-0.13*	-0.09	MKTRF	-0.05	0.01	-0.03	0.09	0.04
	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)		(0.09)	(0.09)	(0.10)	(0.10)	(0.10)
SMB		-0.02	0.03	0.10	0.16	SMB		-0.39**	-0.42**	-0.31*	-0.38**
		(0.13)	(0.13)	(0.14)	(0.14)			(0.16)	(0.17)	(0.18)	(0.18)
HML		0.19**	0.25***	-0.01	0.07	HML		0.29**	0.24*	-0.05	-0.13
		(0.09)	(0.09)	(0.12)	(0.13)			(0.12)	(0.12)	(0.15)	(0.16)
RMW				0.22	0.26	RMW				-0.01	-0.05
				(0.18)	(0.17)					(0.22)	(0.22)
CMA				0.38**	0.33*	CMA				0.81***	0.87***
				(0.19)	(0.18)					(0.23)	(0.23)
MOM			0.20*		0.19*	MOM			-0.14		-0.21
			(0.10)		(0.10)				(0.13)		(0.13)
R-squared	0.04	0.09	0.12	0.14	0.18	R-squared	0.00	0.09	0.10	0.20	0.22

Table 5 (continued)

Panel C: Subsample Results				
	$1_{monetize} = 0$		$1_{monetize} = 1$	
	(1)	(2)	(3)	(4)
	Mean	Alpha	Mean	Alpha
H-L	0.78*	0.86**	-0.34	-0.19
	(0.39)	(0.39)	(0.76)	(0.74)
Mean Diff			(3) - (1)	(4) - (2)
p-value			0.044	0.022

Table 6: Mobile App Disclosure

Panel A reports regression result of firms' mobile app disclosure measure on firm characteristics. The dependent variable is the logged mobile app disclosure measure $log(Dis+1)$. Year fixed effects are included. Standard errors are clustered at the firm level and are presented in parentheses. Panel B reports regression result of earnings on lagged mobile app downloads, subsampled by the median value of the mobile app disclosure measure. Variable definitions are presented in the Appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel B: Determinant Model			
	(1)	(2)	(3)
$1_{monetize}$	0.72***	0.57***	0.48***
	(0.09)	(0.08)	(0.08)
NI/AT		-0.01*	-0.01*
		(0.01)	(0.01)
$\log(SIZE)$		-0.03**	-0.02
		(0.02)	(0.02)
$TrdSecret$		0.17***	0.11***
		(0.04)	(0.04)
$Markup$		-0.04	0.00
		(0.12)	(0.12)
PCM		0.49***	0.41***
		(0.13)	(0.13)
HHI		-0.25**	-0.18*
		(0.10)	(0.10)
BM		-0.02	-0.02
		(0.06)	(0.06)
RD/AT		0.14***	0.12***
		(0.02)	(0.02)
$CAPX/AT$		-0.05*	-0.04
		(0.02)	(0.02)
SGA/AT		0.00	0.01**
		(0.00)	(0.00)
Ind FE	N	N	Y
Obs	6,417	4,732	4,732
R-squared	0.61	0.70	0.71

Table 6 (continued)

Panel B: Earnings Prediction Subsample				
	$dis \leq median$		$dis > median$	
	(1)	(2)	(3)	(4)
	NI/AT_q	NI/AT_q	NI/AT_q	NI/AT_q
$\log(DL/AT)_{-1}$	0.30***	0.24*	0.33**	0.34**
	(0.10)	(0.12)	(0.14)	(0.15)
Firm & Time FEs	Y	Y	Y	Y
Controls	N	Y	N	Y
Observations	12,250	9,131	12,179	10,038
R-squared	0.27	0.51	0.37	0.43

Table 7: Predicting Future SUE and Returns – Subsampled by Disclosure Measure

Panel A reports regression result of SUE (standardized unexpected earnings) on lagged mobile app downloads, subsampled by median firm disclosure. Panel B reports the return predictability results, subsampled by median firm disclosure. Standard errors are clustered at the firm level. Standard errors are shown in parentheses. Variable definitions are presented in Appendix A. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A: Predicting SUE Subsample				
	$dis \leq median$		$dis > median$	
	(1)	(2)	(3)	(4)
	SUE	SUE	SUE	SUE
$\log(DL/AT)_{-1}$	9.72***	9.19**	0.69	0.00
	(3.60)	(4.06)	(2.84)	(3.27)
Firm & Time FE	Y	Y	Y	Y
Lags	Y	Y	Y	Y
Controls	N	Y	N	Y
Observations	8,633	6,336	8,566	7,005
R-squared	0.21	0.23	0.23	0.24
			(3) - (1)	(4) - (2)
			0.031	0.059

Panel B: Predicting Return Subsample				
	$dis \leq median$		$dis > median$	
	(1)	(2)	(3)	(4)
	Mean	Alpha	Mean	Alpha
H-L	1.43***	1.51***	0.45	0.56
	(0.48)	(0.49)	(0.48)	(0.49)
Mean Diff			(3) - (1)	(4) - (2)
p-value			0.009	0.093

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
$1_{monetize}$	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.	ST
Mobile App disclosure measure (dis)	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", "app", "in-app", "download", "user", "ios", and "android".	EDGAR
Mobile App Conference Call Question ($conf$)	the average mentions of app information in the analyst question section of conference calls for a given firm in a given year. The phrases include "mobile application", "app", "in-app", "download", "user", "ios", and "android".	Thomson Reuters StreetEvents
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

Variable	Description	Source
Markup	firm-level marketup 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
Ret	company return from CRSP	WRDS
BM	book-to-market ratio from the financial ratio dataset	WRDS
GPROF	gross profitability measure from the financial ratio dataset	WRDS
DEBT	debt ratio measure from the financial ratio dataset	WRDS
ACCURAL	accural measure from the financial ratio dataset	WRDS

Appendix B: Additional Tables

Table 8: Predicting Future Sales

This table reports the regression results of revenue on lagged mobile app downloads. Firm and time fixed effects are included. 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.

VARIABLES	(1) REV/AT_q	(2) REV/AT_q	(3) REV/AT_q
$\log(DL/AT)_{q-1}$	1.24***	0.56***	0.33*
	(0.20)	(0.16)	(0.18)
REV/AT_{q-1}		0.47***	0.32***
		(0.04)	(0.06)
$\log(AT)_{q-1}$			-3.99***
			(0.42)
BM_{q-1}			-1.26***
			(0.43)
RD/AT_{q-1}			-0.13
			(0.18)
$CAPX/AT_{q-1}$			0.84***
			(0.19)
SGA/AT_{q-1}			0.23**
			(0.10)
Constant	19.36***	10.41***	48.21***
	(0.51)	(0.75)	(4.34)
Firm & Time FEs	Y	Y	Y
Observations	28,091	28,062	28,062
R-squared	0.90	0.92	0.93

Table 9: Predicting Future Earnings with Additional Controls

This table reports the regression results of earnings on lagged mobile app downloads. Firm and time fixed effects are included. 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.

VARIABLES	(1) NI/AT_q	(2) NI/AT_q	(3) NI/AT_q	(4) NI/AT_q
$\log(DL/AT)_{q-1}$	0.16***	0.16***	0.15**	0.15**
	(0.06)	(0.06)	(0.06)	(0.06)
NI/AT_{q-1}	0.22***	0.22***	0.21***	0.21***
	(0.02)	(0.02)	(0.03)	(0.03)
$\log(AT)_{q-1}$	-0.07	-0.06	-0.21*	-0.15
	(0.12)	(0.12)	(0.12)	(0.13)
BM_{q-1}	-1.60***	-1.61***	-1.60***	-1.61***
	(0.15)	(0.15)	(0.15)	(0.15)
RD/AT_{q-1}	-0.09	-0.09	-0.09	-0.09
	(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}	-0.05**	-0.05**	-0.06**	-0.06**
	(0.02)	(0.02)	(0.02)	(0.02)
$INTAN/AT_{q-1}$	-0.01*			-0.01
	(0.00)			(0.00)
SFT/AT_{q-1}		-0.01		
		(0.04)		
GW/AT_{q-1}		-0.01		
		(0.01)		
$INTANO/AT_{q-1}$		-0.00		
		(0.01)		
Q^{tot}_{q-1}			0.05***	0.05***
			(0.02)	(0.02)
Constant	2.03*	1.96*	3.03***	2.72**
	(1.11)	(1.13)	(1.11)	(1.16)
Firm & Time FEs	Y	Y	Y	Y
Observations	19,809	19,809	19,035	19,035
R-squared	0.54	0.54	0.53	0.53

Table 10: Returns on Earnings Announcement Days

This table reports regressions of firms' daily stock returns on the previous log(DL/AT)ab using the whole sample and the samples of the 7-day windows around the firms' earnings announcement dates. Results are based on Fama-MacBeth regression method. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Baseline	7-day
$\log(DL/AT)^{ab}$	0.025**	0.176*
	(0.010)	(0.076)
Obs	1048151	111286

Appendix C: 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

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:

- users increasingly engage with other competitive products or services;
- user behavior on any of our products changes, including decreases in the quality of the user base and frequency of use of our products and services;
- 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 ads that we display;
- there are decreases in user sentiment due to questions about the quality of our user data practices or concerns related to privacy and the sharing of user data;
- there are decreases in user sentiment due to questions about the quality or usefulness of our products or concerns related to safety, security, well-being or other factors;
- users are no longer willing to pay (or pay as much) for subscriptions or in-app purchases, including due to changes to the payment platform or payment methods;
- users have difficulty installing, updating or otherwise accessing our products on mobile devices as a result of actions by us or third parties, such as application marketplaces and device manufacturers, that we rely on to distribute our products and deliver our services;
- we fail to introduce new features, products or services that users find engaging or if we introduce new products or services, or make changes to existing products and services, that are not favorably received;
- we fail to keep pace with evolving online, market and industry trends (including the introduction of new and enhanced digital services);
- we fail to appeal to and engage the younger demographic of users (for example, Gen Z), with their different dynamics of connection;
- initiatives designed to attract and retain users and engagement are unsuccessful or discontinued, whether as a result of actions by us, third parties or otherwise;
- there is a decrease in user retention as a result of users finding meaningful relationships on our platforms and no longer needing to engage with our products;
- third-party initiatives that may enable greater use of our products, including low-cost or discounted data plans, are discontinued;

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

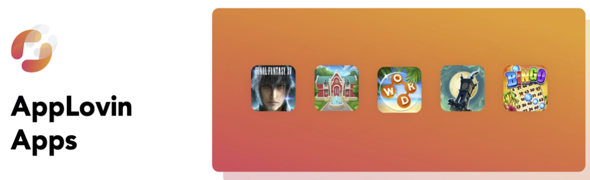
Item 1. Business

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.

Item 8. Financial Statements and Supplementary Data

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