Mobile App, Firm Risk, and Growth

Xi Wu*

July 2023

Abstract

This paper studies the economic value of mobile applications (apps) and their effect on firms, particularly highlighting how these apps, by giving access to customer data, enhance firm-specific information environment. Constructing a unique measure of app value using novel data on all mobile apps of publicly listed firms, we show this measure corresponds positively with the utility value of these apps, as measured by future app downloads. Firms' app values are associated with a significant reduction in firm-specific risk, especially when the apps collect user data and when firms have a poor initial information environment, consistent with recent theories on the role of data for firm risk. Furthermore, firms' app value predicts substantial future growth and increases in market power. Overall, the findings highlight mobile apps as an important digital asset in shaping firm information environment and real outcomes.

Keywords: Mobile Application, Valuation, Data, Risk, Growth, Intangible Capital

JEL-Classification: G14, L1, O3

*Xi Wu is with Haas School of Business, University of California Berkeley. E-mail: xiwu@haas.berkeley.edu.

1 Introduction

Mobile applications (apps), from TikTok and Facebook to Google Maps, have seamlessly integrated into our daily routines. Since their inception over a decade ago, the mobile app market has grown immensely in size and popularity. According to BBC, individuals devote roughly a third of their waking hours, approximately 4.8 hours a day, to apps.[1] This surge in usage has not gone unnoticed by businesses, many of whom have released their own apps over the past decade. These digital platforms allow companies to directly reach customers, facilitating data collection that supports informed decision-making, and have become a vital part of their operations. For instance, Starbucks' introduction of their mobile app greatly increased their data collection, enhancing their understanding of customers and providing invaluable insights into trends and preferences within their customer base.[2] Starbucks is just one among many; in our sample, over 690 U.S. public firms across a majority of industry sectors have released more than 9,600 apps since 2008.[3] Despite the growing importance of the mobile app market, our understanding of its impact on business dynamics remains limited. Leveraging a novel dataset that includes all apps released by U.S. publicly listed firms, and building on recent theories on data and firms, our study is the first to examine the economic implications of mobile apps on firm risk, growth, and market power.

The world of mobile apps is vast and diverse, containing both popular and relatively unknown ones. Some apps, such as Facebook and Youtube, have over a billion users worldwide, while a large proportion of other apps have fewer than a thousand total downloads. To analyze the role of apps for firms, we need a measure that can reflect the differences in

[1]See https://www.bbc.com/news/technology-59952557.

[2]As of 2022, Starbucks' mobile app and rewards program have allowed the company to gather valuable data from over 27 million active users, according to their Q3 2022 earnings call. The data gathered, which includes users' purchasing habits and preferences, plays a crucial role in making key business decisions like determining new store locations, product expansion, and menu updates. Notably, Starbucks uses the data to personalize the customer experience, which they attribute as the largest driver of increased custosmer spend (Q2 2017 Earnings Call). CEO Kevin Johnson also emphasized the value of digital relationships in driving significant long-term value to Starbucks through more frequent occasions, increased spend, improved customer retention and marketing efficiency (Starbucks' Q3 2019 conference call).

[3]Out of 71 two-digit SIC code sectors, 55 sectors have public firms with app releases.

their economic values, and be comparable across industries and across time. To this end, we apply the method of Kogan et al. (2017) to estimate the private economic value of new apps by examining stock market reactions to app releases of publicly listed companies. Because stock prices are forward-looking, this measure estimates the private value to the app owners based on ex ante information, and can be useful in analyzing firm activities. Moreover, this market-based measure can be represented in dollar amount and thus is comparable across different industries and across time.

We first find that around the day of mobile app releases, there are notable increases in the stock trading activity of the firms releasing the apps, indicating that value-relevant information is disseminated to the market. To isolate the stock price movement related to the news of mobile app releases, we use a narrow window (three days) of market reaction following the release date of the apps. However, stock prices may still move for other reasons unrelated to app releases even within this narrow window. To address this concern, we apply similar distributional assumptions as in Kogan et al. (2017) to filter the component of stock returns that is related to the app value from noise.[4] The estimated market-based app value is highly right-skewed. The average mobile app value is $120 million, and the median app value is $24 million. The 1st-percentile and 99th-percentile are $0.09 million and $1.33 billion, respectively. The distribution of the estimated app value and the industries of firms with apps are consistent with data patterns based on venture capital financing for mobile apps and app transactions from online marketplaces in the U.S..[5]

To evaluate the usefulness of our app-value measure, we examine whether it is informative regarding an app's future user adoption, as measured by its average weekly downloads. User adoption is perhaps the most common metric that the industry employs to evaluate the value of an app. According to BuildFire, a mobile app development platform, the number of downloads from the app store is the primary metric most universally used for evaluating the

[4]As pointed out by Kogan et al. (2017), the procedure aims to measure the private economic value of the announced object, which in our case is the mobile app. Although their distributional assumptions are used for a sample of patents, the method is general.

[5]The detail discussion is included in Section 2.3.

value of an app.[6] We find that our app-value measure is strongly and positively associated with the app's average forward weekly downloads. The relationship cannot be explained by a number of observable firm and app characteristics, suggesting that the measure captures a distinct aspect of the economic value of apps. The point estimates show that a one-standard-deviation increase in the logged number of average weekly downloads is associated with a 2.7%–37.3% increase in the mobile app value, depending on the model specifications. The results suggest that the future user adoption of an app is anticipated and reflected in the private value of the app at the time it was released.

Next, we use our app-value measures to examine the economic importance of mobile apps for firms. Since a crucial component of the app value comes from the data it collects (e.g., Scott Morton et al. (2019), Veldkamp (2023)), we focus on how these apps, by giving access to customer data, enhance firm-specific information environment and affect subsequent growth.[7] To that end, we guide our empirical analyses based on the predictions from a growing theoretical literature that highlights the role of data in reducing firm uncertainty and risk (e.g., Farboodi and Veldkamp (2021); Farboodi and Veldkamp (2022); Veldkamp (2023)). Specifically, Eeckhout and Veldkamp (2022) develop a theoretical model studying how firms' use of data may facilitate decision making. Their model suggests that data as digitized information can reduce firm-specific or systematic risks. Importantly, the type of risk alleviated by data can result in divergent outcomes for firm growth and market power. A notable challenge in testing the model predictions is the lack of measure for the data a firm has. Given that apps allow firms to collect customer data and such data are valuable to firms (Veldkamp (2023)), we use our app-value measure to test these theoretical predictions by studying the relationship between mobile app value and different types of firm risks.

Consistent with the prediction that data can reduce firm-specific risks, we find that firms'

[6] See e.g., https://buildfire.com/mobile-app-value/.

[7] Many mobile apps are aggressive in collecting all aspects of information about their customers, which gives rise to heighten debate over data protection and privacy concerns among policy markers and practitioners. For example, the U.S. Federal Trade Commission (FTC) recently indicated their intention to increase data privacy enforcement efforts against mobile apps in the case of GoodRx Holdings (FTC File No 2023090).

app-value measures are negatively and significantly associated with their subsequent changes in firm-specific risk, measured by idiosyncratic volatility.[8] The economic magnitudes are large—a one-standard-deviation increase in the app value is associated with a 1.8% decrease in firm idiosyncratic volatility over a period of five years. The results are estimated with industry and releasing year fixed effects, thus comparing firms within the same industry and the same year. The findings are robust to different definitions of idiosyncratic risks, and remain qualitatively similar when controlling for firms' investment opportunities (Tobin's Q) and a broad set of alternative firm investments, including physical assets, research and development (R&D), labor, advertising and other intangible capital (SG&A), and patents (as per Kogan et al. (2017)). Moreover, the decline in idiosyncratic volatility appears to be permanent, with an increasing trend of risk reduction over an extended period. On the contrary, we do not find a statistically significant association between firms' app-value measures and subsequent changes in their systematic risks.

To strengthen the link between the reduction in firms' idiosyncratic volatility and the data collection of apps, we manually gather information on each mobile app's data collection policy from the iOS App Store. On average, apps that collect user-linked data have a higher estimated economic value than other apps. At the firm-year level, when firms release apps that collect data, they experience a substantial decrease of approximately 7% in idiosyncratic volatility over a horizon of five years, while firms releasing apps that do not collect data experience a reduction of only about 2.7%. In addition, the differences in risk reduction between these two groups of firms increase over time, in line with the increasing returns to data as firms accumulate and use more data (Veldkamp (2023)). These findings provide consistent evidence that mobile apps can reduce firm-specific uncertainties through access to customer data, and such data comprise an essential component of the private economic value of apps.

To further validate our inference that mobile apps reduce firm-specific risk through

[8] We also use cash flow volatility as an alternative measure of firm risk, and find robust and consistent negative relation between firms' app-value measures and subsequent changes in this measure of firm risk.

an improved firm-specific information environment, we conduct two cross-sectional tests. Specifically, we examine whether the effect of apps on firm idiosyncratic volatility is more pronounced for firms with poorer initial information environment, as these firms are likely to benefit more from the acquisition of comprehensive customer data. We use two widely adopted proxies for the amount of firm-specific information in the literature: firm size and analysts coverage (e.g., Hong et al. (2000)). Consistent with our prediction, we find that the effect of apps on firm idiosyncratic volatility is larger when firms have poorer initial information environment–smaller firms and firms with low analyst coverage.

Our results on firm risks suggest that while mobile apps can reduce firm-specific risks, they do not have a significant impact on their systematic risks. Based on the theoretical predictions in Eeckhout and Veldkamp (2022), if data primarily reduces firm-specific risks, there would be an investment-data complementarity channel. That is, because of the reduction in firm-specific risks, firms would optimally increase investment and grow larger, leading to increased market power in their industries. Our analyses provide evidence supporting this theory. First, we find that firms' app-value measures are positively and significantly associated with their investment and profit growth. At the five-year horizon, a one-standard-deviation increase in app value is associated with a 3.2% increase in employment, a 4.7% increase in total assets, a 4% increase in sales, and a 3.2% increase in profit. Second, we show that firms' app-value measures are positively and significantly associated with changes in market power, measured as either their asset share or revenue share in their SIC 4-digit industry (e.g., Rossi-Hansberg et al. (2021); Kwon et al. (2022)). The economic magnitudes are sizable: a one-standard-deviation increase in the app-value measure is associated with a 4% (3.4%) increase in market share based on firms' asset share (revenue share) over a period of five years. These results are robust to controlling for firm investments (physical assets, R&D, SG&A), Tobin's Q, and the Kogan et al. (2017) patent value measure. Together with the previous results, the findings reveal a strong relation between the economic values of mobile apps, firm-specific risk and growth, supporting the theoretical predictions (e.g., Farboodi and Veldkamp (2021); Farboodi and Veldkamp (2022); Veldkamp (2023)).

We conduct additional analyses to investigate the effect of our app value estimates. First, for both our analyses on firm risk and growth, we use an alternative measure of firm-app value based on the number of app downloads, which is considered an important metric for app value in the industry. We find that while the user-download-based app-value measure has a negative and statistically significant relation with changes in firm idiosyncratic volatility, and a positive and statistically significant relation with changes in firm growth and market power, the effect is largely absorbed by the market-based app-value measure. Second, we examine the effect of app value estimates at the extensive and intensive margins separately. At the extensive margin, we find that firms with app releases experience larger reduction in firm risk and higher increase in growth than firms without app releases. At the intensive margin within the sample of firms with app releases, we find that high app-value estimates are associated with larger effect on firm risk and growth than low app-value estimates. Overall, our results highlight the significant role of mobile apps in shaping firm risk, growth, and market power.

This paper relates to several strands of the literature. First, the paper relates to the literature on the digital economy. Goldfarb and Tucker (2019) survey this literature and discuss the unique features of the digital economy. Several papers focus on the effect of information technology on aspects such as product variety (e.g., Anenberg and Kung (2015)), firm organization (e.g., Bresnahan et al. (2002); Bloom et al. (2014)), health care outcomes (e.g., Athey and Stern (2000)). A number of studies examine the impact of the internet, such as political polarization (e.g., Boxell et al. (2017)), education (e.g., Acemoglu et al. (2014)), news (e.g., Athey and Mobius (2012); Allcott and Gentzkow (2017)), e-commerce (e.g., Brynjolfsson and Smith (2000); Bakos (2001); Borenstein and Saloner (2001)) and advertisement (e.g., Arnosti et al. (2016); Athey and Gans (2010); Athey et al. (2013)). However, little is known about the role and implications of mobile apps for firms. In a companion paper, Huang et al. (2022) document a large increase in the market concentration of the mobile app economy and investigate the potential underlying mechanisms. To the best of our knowledge, this study is the first to systematically measure the economic value of apps and examine their effects on firms' information environments, risk, and growth.

Second, this paper contributes to the literature on the economics of data. A growing theoretical literature examines the effects of data on firms. Eeckhout and Veldkamp (2022) investigate how firms' use of data may facilitate decision making. Kirpalani and Philippon (2020) show the importance of data in a two-sided platform model. Ichihashi (2020) studies the role of online consumer data in price discrimination. Several papers emphasize data as information (e.g., Begenau et al. (2018); Acemoglu et al. (2019); Bergemann and Bonatti (2019a); Farboodi et al. (2022); Eeckhout and Veldkamp (2022)). Empirical research examines the role of data in specialized markets such as media (e.g., Athey and Gans (2010); Athey and Mobius (2012)), booksellers (e.g., Brynjolfsson et al. (2003)), and digital technology firms (e.g., Rajgopal et al. (2021)). Several studies use alternative data to forecast firms' fundamentals (e.g., Rajgopal et al. (2003); Katona et al. (2018); Zhu (2019)). However, as discussed in Eeckhout and Veldkamp (2022) and Veldkamp (2023), none of these analyses examine the effects of data on firm risk.

Third, the paper relates to the literature on measuring the value of intangible capital. A number of papers link patenting activities to firms' stock market valuation (e.g., Pakes (1985); Austin (1993); Hall et al. (2005)). The most related work to us is Kogan et al. (2017) that pioneer a new method to extract the private economic value of patents from stock returns. Several papers use these estimated private economic value of patents (e.g., Kogan et al. (2020b); Kogan et al. (2020a); Kelly et al. (2021)). Our paper applies the method of Kogan et al. (2017) to mobile apps to estimate their private economic value. An important distinction between our paper and Kogan et al. (2017), beyond examining a different type of intangible asset, is that we highlight accessing customer data forms an essential component of the private economic value of apps.

The rest of the paper is organized in the following way. Section 2 discusses data and key measurements. Section 3 relates mobile app-value measures to app adoption, as measured by their forward average weekly downloads. Section 4 studies the relation between app values and firm risks. Section 5 examines the relation among mobile app value, firm growth, and market share. Section 6 conducts additional analyses. Section 7 concludes the paper.

2 Data and Measurements

In this section, we first discuss our data sources. Using a unique app dataset, we construct an empirical estimate of the economic value of each mobile app, following the methodology outlined by Kogan et al. (2017). We also investigate the attributes and distribution of app values at both the individual app and firm levels.

2.1 Mobile App and Firm Data

Our primary data source for mobile applications is Sensor Tower (ST), a leading provider of app data and key metrics in the mobile economy. The ST database contains a comprehensive collection of information on millions of mobile applications across more than 100 countries. For the purpose of this paper, we specifically focus on the U.S. market and apps available in the Apple App Store (iOS), with data coverage starting from January 2012.[9]

Because we are interested in the apps owned by publicly listed companies for which we have stock price data, we first identify these apps in the database. ST provides stock tickers for parent companies of apps if the parent companies are listed on major stock exchanges. We download all apps whose parent firms are publicly listed in the U.S. using the linking table from ST. 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 accuracy of each ticker, its corresponding firm name, and the effective dates of the ticker.[10]

[9] We use iOS app data for our main analyses because it offers a longer data period, starting in January 2012, compared to Google Play (Android) apps, where data availability begins in January 2014.

[10] For example, when the publisher name is different from the company name, we search for 10k to get the list of subsidiaries, firm names, and histories of mergers and acquisitions.

In the case of apps that have changed ownership, we only retain the app-parent firm pair at the time of the app's release.

For each app owned by public firms, we obtain the following types of data. The first dataset includes the release date and primary category of each app in the iOS store. The second comprises the estimated total downloads of each app in the US at a weekly frequency, spanning from January 2012 to December 2021. To generate download estimates, ST combines actual data provided by their publisher and developer partners with an array of signals from the App Store, including App Rankings and App Metadata. Using their proprietary data models of the App Store, ST generates daily download estimates for each app. A download is defined as a unique download per iOS account; it does not count re-downloads, app updates, or subsequent downloads on new or additional devices for the same existing iOS account. The third dataset consists of the estimated weekly active users of each app, available from August 2015 to December 2021 for a subset of the apps. An active user is defined as any phone or iPad user that has at least one session during a specific time period. If a user engages in more than one session during the selected time period, they still only count as one active user for that time period. The weekly active user measure counts users that have at least one or more sessions within a week. This active user data is derived from a proprietary panel of over 10 million smartphone users, a large number of actual usage metrics provided to ST by their publisher/developer clients, and a variety of modeling techniques for data extrapolation.

Next, we combine the app data with the CRSP/Compustat merged database, and obtain firms' daily stock return data from CRSP. We require enough return data for computing return volatility and market capitalization. We also require the sample of firm-year observations to have nonmissing values of total assets and SIC industry classification codes. These data requirements yield a main sample of 7,844 apps released between 2008 and 2021.[11] Figure 1 shows the cumulative count of apps in our sample from 2008 to 2021. We discuss

[11] The results are robust to omitting financial (SIC codes 6000 to 6799) and utility (SIC codes 4900 to 4949) firms.

each measure in greater detail in the corresponding analysis section.

2.2 Estimating the Market Value of a Mobile App

To estimate the market value of each mobile app, we apply the methodology developed by Kogan et al. (2017), which is a general method that can be applied to various informational events. In our context, the events are the releases of mobile apps, and we estimate and calibrate the parameters of the method specifically for our case. We outline the estimation procedure in the main text and provide more details in the Internet Appendix. For a complete explanation of the method, we refer interested readers to Kogan et al. (2017), where they develop the method to estimate the value of patents.

The idea is to use the stock market reaction around a mobile app release to infer the market value of the app. On the day of the mobile app release, investors learn that the app is officially released and update their information set about the company and trade accordingly. Therefore, the firm's stock price would react to the news of the app release: if the market value of the mobile app is higher, we would expect a stronger market reaction and vice versa. In theory, if the stock market is fully efficient, we would anticipate an instantaneous reaction to the news of the mobile app release. However, a large stream of literature (e.g., Ball and Brown (1968); Bernard and Thomas (1989); Liu and Wu (2021)) documents that it takes time for the stock market to fully incorporate news. Therefore, following Kogan et al. (2017), we use a three-day window starting from the event date to capture the stock market reaction.[12] In untabulated results, we confirm that the stock trading activity–measured by either abnormal trading volume or share turnover–of firms releasing apps significantly increases around the release day, suggesting the dissemination of value-relevant information to the market.

[12] A proportion of the apps (approximately 11%) are released on the weekend. In such cases, we consider the subsequent Monday as the release day to match with return data. The results are robust if we drop these weekend app releases. The results are also robust if we use calendar days around app releases to match with return data instead of trading days. Furthermore, our findings hold up when using alternative event windows, such as a five-day window.

To provide an illustrative example, based on Sensor Tower, Netflix released its Netflix app for download on iPad in the App Store on April 1, 2010. The firm's stock price increased by 11% above the stock market during the three-day window starting from the app's release date. The large increase in Netflix's stock price reflects that investors held an optimistic view of the app's potential success and believed the app had a high market value. Media sentiment mirrored this positive outlook. For example, the *New York Times* noted on April 1 that the "Netflix app would be a perfect fit for the iPad." As it transpired, the app proved to be a great success, achieving an average weekly download of about 300,000 throughout our sample period.

In the absence of other information, stock market returns around the mobile app release would capture the market value of the mobile app as a fraction of the market capitalization of the firm. However, stock prices might fluctuate during the announcement window for reasons unrelated to the mobile app. Specifically, during the three-day event window, both aggregate market news and firm-specific news that are unrelated to the mobile app release could occur. Therefore, an important step in constructing the mobile app value is to isolate the component of the firm's return around the mobile app release that is solely related to the value of the mobile app.

First, to remove aggregate market news, we use the firm's idiosyncratic return, calculated as the difference between the firm's return and the return on the market portfolio, as proposed by Kogan et al. (2017). This definition of idiosyncratic return assumes that firms have a constant beta loading of one with the market, and the benefit of this definition lies in its simplicity, as it avoids estimating factor loadings.

Second, around the event of the mobile app release, the idiosyncratic stock return still contains two components—a component related to the mobile app release and a component unrelated. To empirically estimate the former component, which is the filtered app value ($E\left[\upsilon|R_f\right]$) where R_f is the stock return for firm f and υ is the app value, we make the same distributional assumptions for the two components as in Kogan et al. (2017), the details of which are presented in the Internet Appendix. In addition, the procedure requires estimating two parameters, $\sigma^2_{\epsilon ft}$ and $\sigma^2_{\upsilon ft}$, which are the volatility of the distribution of the return component related to mobile app release and the volatility of the distribution of the return residual component, respectively. To estimate the two parameters, we first assume that the signal-to-noise ratio, $\frac{\sigma^2_{\upsilon ft}}{\sigma^2_{\upsilon ft}+\sigma^2_{\epsilon ft}}$, is a constant of 0.0145 across firms and time as specified in Kogan et al. (2017).[13] With this assumption, we only need to estimate one of the two parameters. In particular, we estimate $\sigma^2_{\epsilon ft}$, which we calculate non-parametrically using the realized mean idiosyncratic squared returns and the fraction of trading days that are announcement days in our sample. We also allow the estimate to vary at an annual frequency.

Lastly, the economic value of a mobile app in dollar, denoted as ξ, is calculated as the product of the component related to the mobile app release ($E\left[\upsilon|R_f\right]$), and the market capitalization of the firm. If multiple mobile apps are released by the same firm on the same day, we assign each mobile app a fraction of the total value equal to one divided by the number of mobile apps released by the same firm on that day. We further assume that the market does not anticipate the successful release of an app before the actual release date. This assumption, that the release is fully unexpected, likely underestimates the value of mobile apps as the releases of some mobile apps may be anticipated. That is, our estimate should be considered as a lower bound of the actual economic value of apps.

2.3 Summary Statistics of Mobile App Value

Table 1 reports the sample distribution of the app value estimates (ξ), the market-adjusted firm returns on the three-day window following the app release date (R), the filtered app-value-related component of returns ($E\left[\upsilon|R_f\right]$), as well as the forward average weekly number of downloads (D).[14] The average (median) idiosyncratic firm return (R) is 0.13%

[13]In Section 6.3, we re-estimate the signal-to-noise ratio using our sample to construct the app value measure. The results remain similar.

[14]Please refer to the Internet Appendix for the detailed estimation process of the app value estimates (ξ) and the filtered app-value-related component of returns ($E\left[\upsilon|R_f\right]$).

(0.00%), which is highly right-skewed. The distribution of the filtered component of returns related to the app value has a mean of 0.29% and a median of 0.26%. The apps display considerable cross-sectional variation in estimated economic value, with a standard deviation of $308.54 million. The average (median) estimated app value is $119.76 ($24.31) million. The 1st percentile of apps has a value of only $0.09 million, while the 99th percentile of apps has a value of $1,326.72 million. In Appendix A.1, we show summary statistics of the estimated app value by app categories. There is substantial heterogeneity in the mean app value across categories. The top five categories with the highest average estimated app value are Photo & Video, Productivity, Health & Fitness, Social Networking, and Business. The bottom five categories with the lowest average estimated app value are Weather, News, Games, Sports, and Travel.

Data on the value of apps are largely unavailable, making it challenging to assess the reliability of our estimated numbers. Nevertheless, we attempt to offer two comparisons. The first comparison is based on the actual mobile app transactions. On the one extreme, Mobile app acquisitions made by public companies can be worth hundreds of millions or even billions of dollars. For example, Facebook (now Meta) acquired Instagram, which is largely an app company, for approximately $1 billion in 2012, and then WhatsApp for $19 billion in 2014. Google (now Alphabet) acquired Waze, a social traffic and navigation app, for a reported price of around $1.3 billion in 2013. Apple acquired Shazam, a music recognition app, for $400 million in 2018. At the same time, according to online marketplaces where app developers can list their apps for sale, the average price of app sales in November 2022 was $0.43 million from Smergers.com and $0.38 million from Flippa.com.[15] We should note that our estimates are higher than the transaction data from the online marketplaces as the apps in our sample are owned by public firms and tend to be attached to higher valuations. In addition, the distribution of our estimated app values is consistent with the actual app sales, where both exhibit large skewness.

[15] Historical transaction data is unavailable from the marketplaces.

Another point of comparison is based on venture capital (VC) financing for mobile app start-ups in the U.S. from the Preqin Venture Deals Database. Preqin is a leading provider of data on alternative assets. The average (median) total funding for an app company is \$51.7 (\$7.2) million. The 1st-percentile and 99th-percentile are \$0.03 million and \$0.724 billion, respectively. In terms of industry distribution, 68% of the apps are in the "Information Technology" category, followed by "Consumer Discretionary" (9%), "Healthcare" (7.6%), and "Financial & Insurance Services" (6.1%). Although the average funding amount is lower than our estimated app value, it is only a fraction of the total value of an app company. For example, according to Crunchbase.com, the average level of VC ownership at exit is 50%. Although the apps in Preqin are not all at the exit stage, assuming a conservative estimate of 50% VC ownership on average would imply an estimated value of \$103.4 (\$14.4) million for the average (median) app, making it comparable to our estimated app values.

Additionally, our estimates could be an underestimation of the actual value of mobile apps, given the fact that we assume that the announcement is fully unanticipated. Even if the average valuation is underestimated, the cross-sectional dispersion in value across different mobile apps remains meaningful. Importantly, in Section 3, we show that the mobile app-value measure significantly and positively correlates with a common and important measure of mobile app quality—the forward average app downloads.

2.4 Firm-Level Measures of Mobile App Value

Our goal is to study the economic value of apps and their effects on firms. To this end, we need a firm-level measure of app value. We first combine the mobile app data with the CRSP/Compustat database. We restrict the sample to firm-year observations with non-missing values of lagged assets and SIC classification codes. If a SIC 4-digit industry has no mobile app released in our sample, we omit the industry. We winsorize all variables at the 1% level by year.

We construct two measures of firm-level mobile app value—the first one is based on our market-based app-value measure, and the second one is based on the forward average weekly app downloads. We measure the first firm-level mobile app value by summing up the market value of mobile apps ξ_j released by a given firm i in year t:

$$v_{i,t}^{sm} = \frac{\sum_{j \in M_{i,t}} \xi_j}{AT_{i,t-1}}, \tag{1}$$

where $M_{i,t}$ denotes the set of mobile apps released by firm i in year t. $AT_{i,t-1}$ is the lagged firm total asset value, which we use as a scaler to adjust for the fact that larger companies tend to have more mobile apps that are of higher quality.[16]

Our second measure is based on the number of app downloads, which is considered an important metric for app value in the industry:

$$v_{i,t}^{dw} = \frac{\sum_{j \in M_{i,t}} \frac{D_j}{\bar{D}_j}}{AT_{i,t-1}} \tag{2}$$

where $\bar{D}_j$ is the mean of the forward average weekly downloads of the apps that are released in the same year as app j. We use this scaling because average weekly downloads may differ based on the life cycle of the mobile apps. Similarly, we scale the measure by the corresponding lagged total asset value.

We present the summary statistics of firm-level measures in Table 2. The table reports the two firm-level mobile app-value measures, as well as logged firm size, idiosyncratic volatility, and the logged growth rates of idiosyncratic volatility, sales, employment, EBIT, EBITDA, and total assets. Both of the two firm-level mobile app-value measures (v^{sm} and v^{dw}) are highly right-skewed and their median values are zero, suggesting that mobile apps' releasing events are not common and that most companies do not have mobile apps released in a given period. Examining the growth rate measures, we see that there is a large dispersion in firm growth rates as measured by sales, profits, labor, and total asset. The distribution of the average firm-level app-value measures reveals substantial heterogeneity across industries.

[16]The results are similar if we scale by the firm's market capitalization.

Based on Fama-French 30 industry classifications, the most app-intensive industries are personal and business services, while the least app-intensive ones are utilities, petroleum, and natural gas.

3 Mobile App Value and Forward Downloads

We first evaluate the usefulness of our app-value measure. Given that the value of a mobile app is inherently challenging to quantify, there is no existing measure to compare with. In the market of mobile apps, a commonly-used and important metric for indicating the value of mobile apps is the forward average number of weekly downloads. This metric assesses user adoption of the mobile app and is frequently used by venture capital and private equity firms when determining the value of companies primarily operating in the mobile app economy.[17]

In this section, we study the relationship between our estimated economic value of mobile apps and their user adoption, measured by the forward-realized average number of weekly downloads.[18] Specifically, we relate the future average number of weekly downloads D_j an app has to the app value ξ estimated in Section 2:

$$\log \xi_j = \alpha + \beta \times \log \left(D_j \right) + \gamma \times Z_j + \epsilon_j. \tag{3}$$

To account for omitted factors that may affect downloads and the measured app value, we include various controls Z_j depending on the model specifications. These controls include the logged firm size, firm idiosyncratic volatility, app release-year fixed effects, and year-app category fixed effects. The logged firm size, measured prior to the app release, is included as larger firms may produce more valuable mobile apps. We include idiosyncratic volatility as

[17] For example, at online marketplaces where app developers can list their apps for sale, such as Smergers.com and Flippa.com, the average user downloads are listed as a key indicator for the value of an app.

[18] The research design is in a similar spirit to Kogan et al. (2017), where they regress patent value on future citations the patent receives. In addition, the results are robust to using alternative measures of download for each app, including the average daily downloads and total downloads.

it directly enters the construction of our measure and more volatile firms may produce more valuable mobile apps. The inclusion of mobile app release-year fixed effects is motivated by the fact that the average number of downloads may vary for mobile apps in different life cycles and that older apps may have differential ability to attract users than younger apps. App category-year fixed effects are included to control for differences in user adoption across app categories over time. We cluster the standard errors by mobile app release year to account for the potential serial correlation of the average number of downloads for mobile apps released in the same year.

As a graphical demonstration, Figure 2 plots the forward average weekly downloads and mobile app value. For ease of interpretation, we group mobile app data into 30 quantiles based on the variable on the x-axis and plot the average downloads in each quantile versus the average estimated app value in each quantile. Panel A shows the relation in raw measures. Panel B shows the result where the average weekly downloads are scaled by the median average weekly downloads of apps in the same year cohort, and the market-based app value is also scaled by the median value of the mobile apps released in the same year. The graph shows an almost monotonically increasing and log-linear relation between the average weekly downloads and the market-based app value measure.

Table 3 presents the regression results from estimating equation 3. We find a positive and highly statistically significant relationship between the forward average weekly downloads and the estimated mobile app value. In the specification without any controls in column (1), the point estimate on $\log(\boldsymbol{D})$ is 0.17. A one-standard-deviation increase in $\log(\boldsymbol{D})$ is associated with a 37.3% increase in the value of the corresponding mobile app. When we include firm size, firm idiosyncratic volatility, and time-app category fixed effect as controls in column (9), the point estimate on $\log(\boldsymbol{D})$ decreases to 0.012 but remains statistically significant at the 1% level. In this specification, a one-standard-deviation increase in $\log(\boldsymbol{D})$ is associated with about a 2.7% increase in the value of the corresponding mobile app.[19] An

[19]Results are similar when only considering apps released after 2012, which is the beginning of the app download dataset.

alternative app-based metric for the value of mobile apps is the number of active users.[20] In Appendix Table A.2, we repeat the analysis using the forward average number of weekly active users of the apps and reach similar results.

Overall, the app-value measure is economically meaningfully related to future app downloads. Nevertheless, it is important to note that the mobile app-value measure and the forward average weekly download likely capture overlapping yet distinct aspects of mobile app quality. In line with Kogan et al. (2017), the estimation procedure aims to measure the private economic value of the announced object, which in our case is the mobile app, while the forward average weekly download captures the actual adoption of the mobile app. For example, a mobile app may only target and attract a small number of users and thus have moderate average weekly downloads, but it is highly addictive and can still generate large private benefits for the company. This distinction has similarities to the difference between the private value and scientific value of patents as discussed in Kogan et al. (2017).

4 Mobile App Value and Firm Risk

In this section, we use our app-value measures to examine the economic importance of mobile apps for firms. As highlighted in Scott Morton et al. (2019) and Veldkamp (2023), a key component of app value stems from the data it collects. Accordingly, we focus on how these apps, by facilitating access to customer data, alter the company-specific information environment and influence subsequent growth. In doing so, we shape our empirical analyses according to the predictions from a growing theoretical literature that underscores the role of data in reducing firm uncertainty and risk (e.g., Farboodi and Veldkamp (2021); Farboodi and Veldkamp (2022); Veldkamp (2023)). Specifically, Eeckhout and Veldkamp (2022) investigate how firms' usage of data might assist in the decision-making processes. Their model proposes that data, as digitized information, can reduce firm-specific or systematic risks.

[20]For example, Meta discussed in its 2022 annual report that its financial performance has been and will continue to be significantly determined by its success in adding and retaining active users in mobile apps.

Importantly, they differentiate between potential reductions of firms' idiosyncratic risk and systematic risk and show that these two types of risk reductions have distinct implications for firm growth and market power. In particular, a reduction in firms' idiosyncratic risk increases their market power, while a reduction in firms' systematic risk leads to increased competition and decreased market power. Equipped with our firm-level app-value measures, we examine these theoretical predictions by investigating the relationship between mobile app value and various types of firm risks. In subsequent sections, we further examine the relation between the app-value measures and firm growth or market power.

We test the relation between the economic value of apps and firm risk using the following specification, and we do so separately for firm idiosyncratic risk and systematic risk:

$$y_{i,t+\tau} - y_{i,t} = \beta \times v_{i,t} + \gamma \times Z_{i,t} + \epsilon_{i,t+\tau}, \tag{4}$$

where $v \in \{v^{sm}, v^{dw}\}$ and y is the logged firms' idiosyncratic risk or systematic risk. Measuring firms' idiosyncratic risk requires choosing a factor model. Because there is no consensus on the appropriate factor model, we use several common models and show that the results are robust to the choices of factor models. In particular, we calculate firm-level idiosyncratic volatility using one of the Fama-French 3-factor, Fama-French 3-factor plus the momentum factor, Fama-French 5-factor, and the Fama-French 5-factor plus the momentum factor models. We use market beta as the systematic risk measure. The horizon τ ranges from one to five years. We include a number of controls $Z_{i,t}$, including the firm's lagged logged size and lagged idiosyncratic volatility, to alleviate the concern that firm size and volatility may drive some mechanical correlation between the dependent variable and app-value estimates. We also include time fixed effects and industry fixed effects using 4-digit SIC codes and cluster standard errors by firm. We normalize firm-level mobile app value to have a mean of zero and a standard deviation of one, so that the point estimates are comparable across different specifications. We also multiply the dependent variable by 100 to be in percentage for ease of interpretation of the coefficient estimate. [21]

4.1 Idiosyncratic Volatility

We first study the relation between firm-level market-based app-value measures and firm idiosyncratic volatility. Specifically, we focus on β in the regression model, which captures the effect of mobile apps on reducing firm idiosyncratic volatility. Table 4 presents the results. Columns (1) to (4) report results of firm idiosyncratic volatility calculated based on the Fama-French 3-factor, Fama-French 3-factor plus the momentum factor, Fama-French 5-factor, and the Fama-French 5-factor plus the momentum factor models, respectively. The results suggest that subsequent changes in firm idiosyncratic volatility are negatively and strongly associated with firm's mobile app-value measure, where all the point estimates are statistically significant at the 1% level. The magnitudes implied by the point estimates are economically large. For example, over a five-year horizon, a one-standard-deviation increase in v^{sm} is associated with about a 1.8% decrease in firm idiosyncratic volatility. There is no reversal in the decline of idiosyncratic volatility, suggesting that the decrease is permanent. In Table A.3 of the Internet Appendix, we show that the results are qualitatively similar after controlling for firm investments (physical assets, R&D, SG&A), Tobin's Q, and the Kogan et al. (2017) patent value measure.

Next, we compare the market-based measure of app value (v^{sm}) with the download-weighted app-value measure (v^{dw}). Table 5 reports the results. Panel A of Table 5 shows the results of regressing changes in idiosyncratic volatility on the download-weighted app-value measure (v^{dw}). The results show that changes in future idiosyncratic volatility are negatively and largely significantly associated with v^{dw}. When comparing the coefficient estimates of β to those in Table A.3, we find them to be smaller in magnitude, about less than half. For example, at the five-year horizon, a one-standard-deviation increase in v^{dw} is associated with

[21] In robustness analyses, we include controls for a wide range of firm investments (physical assets, R&D, SG&A), Tobin's Q, and the Kogan et al. (2017) patent value measure. As discussed later, results are robust to alternative model specifications and app value estimates.

about a 0.9% decrease in idiosyncratic volatility.

Importantly, we find that the significance of v^{dw} in predicting changes in future idiosyncratic volatility is largely absorbed by v^{sm}. Panel B of Table 9 includes both measures as predictors to examine whether these two measures contain independent information regarding firms' future changes in idiosyncratic volatility. When both v^{sm} and v^{dw} are included, the coefficient estimates on v^{sm} remain highly statistically significant, while the coefficient estimates on v^{dw} are largely statistically insignificant. The point estimates on v^{sm} are similar to those in Table A.3 and are economically large. For example, at the five-year horizon, the point estimates suggest that a one-standard-deviation increase in v^{sm} is associated with about a 1.7% decline in idiosyncratic volatility.

In summary, the mobile app-value measures are significantly associated with a reduction in firm-specific risks. This risk reduction effect highlights the unique feature of mobile apps compared to traditional firm products and services. Mobile apps are a product that firms can use to actively collect data from customers and, in turn, improve firm-specific information environment and reduce their own uncertainty. The fact that the market-based app-value measure outperforms the download-weighted app-value measure in predicting changes in firm-specific risks suggests that the market-based measure contains substantially additional information relative to the common industry practice of using mobile apps' number of downloads to infer their value, and this additional information is most likely related to private values associated with releasing mobile apps.[22]

4.2 Data Collection of Mobile Apps

Our results reveal that firms' mobile app value is negatively associated with their idiosyncratic volatility in the future, consistent with the theoretical prediction of Eeckhout and Veldkamp (2022) given that an important component of the app value comes from the

[22]In Table A.4 of the Internet Appendix, we use synchronicity as a measure of firm stock market informativeness. We find that the firm app-value measures lead to an increase in synchronicity, which is consistent with the view that mobile apps lead to a reduction in firm-specific risks.

data it collects. In this subsection, we provide further evidence of the importance of data collection of mobile apps in driving the reduction in firms' idiosyncratic volatility. To identify whether the mobile apps in our sample collect user-linked data, we hand-collect information on each mobile app's data collection policy from the iOS App Store. For each firm in a given year, we define an indicator variable ($1_{\{Data\}}$) that equals one if the firm releases an app and at least one of the mobile apps released collects data linked to users, and zero otherwise. For firms that release apps that do not collect data, we designate an indicator variable ($1_{\{Other\}}$) for these firms.

Pane A of Table 6 reports the summary statistics of firm app-value measures with or without data collection. On average, apps that collect user-linked data have a higher estimated economic value than other apps, about twice of their value. In Panel B of Table 6, we test the relation between data collection and firm risk using the following specification:

$$y_{i,t+\tau} - y_{i,t} = \beta^{Data} \times 1_{\{Data\}} + \beta^{Other} \times 1_{\{Other\}} + \gamma \times Z_{i,t} + \epsilon_{i,t+\tau}, \tag{5}$$

where the benchmark are the firm-year observations without app releases. We report the point estimates of $1_{\{Data\}}$ and $1_{\{Other\}}$ from one-year to five-year horizons. β^{Data} is consistently larger than β^{Other} over all horizons and across different measures of idiosyncratic volatility. The gap between β^{Data} and β^{Other} also tends to increase over the horizons. For example, based on the Fama-French 5-factor model, firm idiosyncratic volatility decreases by 7% for companies that release apps that collect user-linked data at the five-year horizon, while it only decreases by 2.7% for companies that release other apps. Overall, having access to customer data comprises an essential component of the private economic value of apps, and such data plays an important role in reducing firm-specific risks, consistent with the theoretical predictions of Eeckhout and Veldkamp (2022).

4.3 Cross-section on Initial Information Environment

To further test the hypothesis that our estimated app value could reduce firm idiosyncratic volatility through an improved firm-specific information environment, we conduct two cross-sectional tests. Specifically, we examine whether the relation between app-value measures and firm idiosyncratic volatility differs across firms with varying amounts of firm-specific information available at the time of app releases. We predict that firms with poorer initial firm-specific information environments experience larger reductions in firm risk following app releases than other firms, because these firms are likely to benefit more from the acquisition of comprehensive customer data.

We follow the literature and use two widely adopted proxies for the amount of firm-specific information: firm size and analyst coverage (e.g., Hong et al. (2000)). We then partition the sample based on either firm size or analyst coverage of the prior year. Table 7 presents the results. Panels A and B report cross-sectional results based on firm size and analyst coverage, respectively. We report results using a three-year horizon, and each row shows a result based on a specific factor model. $\boldsymbol{Large}$ ($\boldsymbol{High}$) is an indicator variable that equals one if the firm size (the number of analysts following) is above the sample median and zero otherwise. The coefficient of interest is on the interaction term between firm-app-value estimate v^{sm} and the subsample variable. Panel A shows that the point estimates on $v^{sm} \times \boldsymbol{Large}$ are positive and statistically significant, suggesting that small firms experience a larger reduction in firm idiosyncratic volatility than large firms following app releases. The economic magnitude is large. Panel B shows that the point estimates on $v^{sm} \times \boldsymbol{High}$ are positive and statistically significant, suggesting that the relation between app-value measures and firm idiosyncratic volatility is more pronounced for firms with low analyst coverage.[23]

Overall, consistent with our prediction, the results suggest that the relation between mobile app value and changes in firm-specific risks is stronger for firms with poorer initial information environments–smaller firms and firms with low analyst coverage.

[23] The results are similar if we compare the coefficient estimates of v^{sm} using separate subsamples.

4.4 Systematic Risk

We next study the relation between the firm-level market-based app-value measure and firm systematic risk as measured by market beta based on Fama-French 3 factor model.[24] Table A.5 in the Internet Appendix presents the results. The results suggest that changes in subsequent market beta are not statistically significantly associated with firms' app-value measures in the specifications using v^{sm} only or v^{dw} only. The magnitudes are also economically small. For example, at the four-year horizon, a one-standard-deviation increase in v^{sm}or v^{dw} is associated with only a 0.002 decrease in the firm's market beta, while a one standard-deviation increase in v^{dw} is associated with no change in the firm's market beta. When both v^{sm} and v^{dw} are included, the coefficient estimates on v^{sm} and v^{dw} remain economically small and statistically insignificant.

Overall, our results suggest that the mobile app-value measure is significantly and negatively associated with firms' idiosyncratic volatility, but is not significantly related to firms' market beta. This implies that data collected through mobile apps mainly reduces firm-specific volatility, but not systematic risk of firms. Based on the theoretical predictions in Eeckhout and Veldkamp (2022), the results suggest an increase in firm growth and market power, which we test in the following section.

5 Mobile App Value, Firm Growth, and Market Share

Eeckhout and Veldkamp (2022) predict that if data primarily reduces firm-specific risks, these firms would invest more, grow faster, and as a consequence, have more market power. Building on our previous findings, in this section, we examine whether the economic value of apps is positively associated with firm growth and market share. To test these theoretical predictions, we use both market-based and download-based app-value measures.

[24]Using alternative factor models generate similar results.

5.1 Mobile App Value and Firm Growth

Using the firm-level app-value measure, we examine the relationship between this measure and firm growth. Specifically, we use the same regression specifications as in the previous section to examine a firm's cumulative growth over multiple horizons:

$$y_{i,t+\tau} - y_{i,t} = \beta \times v_{i,t} + \gamma \times Z_{i,t} + \epsilon_{i,t+\tau}, \tag{6}$$

where $v \in \{v^{sm}, v^{dw}\}$. y is the logged version of one of the following variables: (1) sales, (2) employment, (3) EBIT, (4) EBITDA, and (5) total assets. These variables cover a wide range of growth measures of a firm, including output, profit, labor, and total assets. The horizon τ ranges from one year to five years. We include a number of control variables $Z_{i,t}$, including the firm's lagged logged size, lagged idiosyncratic volatility, time and industry fixed effects, and cluster standard errors by firm. We normalize firm-level mobile app value to have a mean of zero and a standard deviation of one so that the point estimates are comparable across different specifications.

First, we study the relation between the firm-level market-based app-value measure and firm growth. Table 8 presents the results. Columns (1) to (5) report results of firm growth measured by sales, employment, EBIT, EBITDA, and total assets, respectively. The results suggest a strong and positive association between future firm growth and the firm's mobile app-value measure, with all point estimates being statistically significant at the 1% level. The magnitudes implied by the point estimates are economically large. For example, at the five-year horizon, a one-standard-deviation increase in v^{sm} is associated with a 4.0% increase in sales, a 3.2% increase in employment, a 3.2% increase in profit, and a 4.7% increase in total assets. There is no reversal in the cumulative firm growth five years out. The results show that the app-value measure is related to firm growth, which can lead to persistent and permanent differences among firms. The results suggest that in the modern digital economy, firms' mobile apps are an important determinant of firms' growth rates. In Table A.6 of the Internet Appendix, we show that the results are qualitatively similar after controlling for firm investments (physical assets, R&D, SG&A), Tobin's Q, and the Kogan et al. (2017) patent value measure.

Next, we compare the market-based measure of mobile app value (v^{sm}) with the download-weighted app-value measure (v^{dw}). Table 9 reports the results. Panel A of Table 9 shows the results of regressing future cumulative firm growth on the download-weighted app-value measure (v^{dw}). The results reveal a strong and generally significant positive association between future cumulative firm growth and v^{dw}. For example, at the five-year horizon, a one-standard-deviation increase in v^{dw} is associated with a 2.2% increase in sales, a 2.0% increase in employment, about a 2% increase in profit, and a 2.6% increase in total assets. The results are consistent with the common industry practice of using app adoption to infer the app's value.

Panel B of Table 9 includes both measures as predictors to examine whether these two measures contain independent information regarding firms' future growth. When both v^{sm} and v^{dw} are included, the coefficient estimates on v^{sm} continue to be highly statistically significant, while most of the coefficient estimates on v^{dw} are either statistically insignificant or significant at the 10% level. The point estimates on v^{sm} also remain economically large. For example, at the five-year horizon, the point estimates suggest that a one-standard-deviation increase in v^{sm} is associated with a 3.7% increase in sales, a 2.8% increase in employment, about a 3% increase in profit, and a 4.3% increase in total assets.

In summary, these findings show that the market-based app-value measure contains substantially more information compared to the prevalent industry practice of using the number of app downloads to infer their value. Importantly, the results are consistent with the theoretical predictions.

5.2 Mobile App Value and Market Share

Finally, we test the relation between mobile app-value measures and changes in firms' market power. We measure firm market power using a firm's asset share or revenue share within their respective SIC 4-digit industry. Both measures are commonly used in the literature to proxy for firms' market power (e.g., Rossi-Hansberg et al. (2021); Kwon et al. (2022)).

Table 10 presents the results. Panels A and B report results using firms' asset share and revenue share, respectively. When evaluated independently, both the market-based and the download-weighted app-value measures show a positive and statistically significant association with changes in future firm market shares. For example, at the five-year horizon, a one-standard-deviation increase in v^{sm} corresponds to an approximate 4.0% increase in market share based on firms' asset share and a 3.4% increase based on firms' revenue share. A one-standard-deviation increase in v^{dw} is associated with about a 2.1% increase in market share based on firms' asset share and a 1.8% increase based on firms' revenue share. In Table A.6 of the Internet Appendix, we show that the results are qualitatively similar after controlling for firm investments (physical assets, R&D, SG&A), Tobin's Q, and the Kogan et al. (2017) patent value measure.

When we include both v^{sm} and v^{dw}, the coefficient estimates on v^{sm} remain highly statistically significant, while those on v^{dw} are no longer statistically significant at any horizon. The point estimates on v^{sm} are economically large and overshadow the significance of v^{dw}. For example, at the five-year horizon, the point estimates suggest that a one-standard-deviation increase in v^{sm} is associated with about a 3.8% increase in market share based on firms' assets share and a 3.2% increase based on firms' revenue share.

Overall, we show a positive and significant relation between our app-value measures and changes in firms' market power as measured by their market shares. The market-based app-value measure completely subsumes the effect of the download-weighted measure. These results are largely consistent with the predictions in Eeckhout and Veldkamp (2022) on the investment-data complementarity channel in increasing the market power of firms.

6 Additional Results and Robustness Checks

In this section, we present additional results and robustness checks. First, we show that the app-value measures are associated with a reduction in firms' cash flow volatility. Next, we find that the app-value estimates of a firm's competitors do not associate with its growth. We also examine the sensitivity of our results by modifying the parameters used in estimating mobile app value. Lastly, we examine the effect of app value estimates at the extensive and intensive margins separately.

6.1 Cash Flow Volatility

In our main results, we use stock returns to measure firm volatility. The advantage of using return volatility is that return data are available daily, enabling us to measure return volatility with relative precision. However, returns capture news not only about a company's cash flows but also about discount rates. Therefore, in this subsection, we use an alternative measure of firm volatility–the cash flow volatility–to study the relationship between mobile app value and changes in firm volatility. The benefit of using cash flow volatility is that it is not affected by changes in firm discount rates.

We measure a firm's cash flow volatility as the standard deviation of its trailing cash flows, using a trailing window of three years or twelve quarters. We measure cash flows as the operating income before depreciation scaled by either lagged assets (CF^{at}) or lagged sales (CF^{sale}). We test the relationship between app-value measures and changes in cash flow volatility using the following specification:

$$y_{i,t+\tau} - y_{i,t} = \beta \times v_{i,t} + \gamma \times Z_{i,t} + \epsilon_{i,t+\tau}, \tag{7}$$

where $v \in \left\{v^{sm}, v^{dw}\right\}$ and y is the logged versions of firms' cash flow volatility. Because we use data from the trailing three years to measure cash flow volatility, we require a three-year gap, or $\tau >= 3$. The results are documented in Table 11.

We observe a negative and statistically significant association between v^{sm} and future changes in cash flow volatility. The results are qualitatively similar using either CF^{at} or CF^{sale}. For example, using CF^{at}, we find that a one-standard-deviation increase in v^{sm} is associated with a 1.9% decrease in cash flow volatility at the five-year horizon. When both v^{sm} and v^{dw} are included, the coefficient estimates on v^{sm} remain highly statistically significant and economically large, while the coefficient estimates on v^{dw} are largely insignificant. For example, at the five-year horizon, the point estimates suggest that a one-standard-deviation increase in v^{sm} is associated with about a 1.8% decrease in cash flow volatility, which is statistically significant at the 1% level.

6.2 Competitors' Mobile App and Firm Growth

We also examine whether the growth of a company is affected by its competitors' mobile app value. To do this, we calculate the app value by competing firms. We define a firm's competitors as other firms in the same SIC 4-digit industry. Therefore, the app value of a firm i's competitors in year t is:

$$v_{I\backslash i,t} = \frac{\sum_{i' \in I\backslash i} \sum_{j \in M_{i,t}} \xi_j}{\sum_{i' \in I\backslash i} AT_{i',t-1}}, \tag{8}$$

where $I\backslash i$ denotes the set of firms in the same SIC 4-digit industry I excluding firm i.

To study the relationship between competitor app releases and firm growth, we use the following regression specification:

$$y_{i,t+\tau} - y_{i,t} = \beta \times v_{I\backslash i,t} + \gamma \times Z_{i,t} + \epsilon_{i,t+\tau}. \tag{9}$$

Similarly, we study cumulative firm growth up to five years ahead, with τ ranging from one to five years.

The regression results are summarized in Table A.8 in the Internet Appendix. The point estimates are largely insignificantly different from zero across different horizons and measures of firm growth. The economic magnitudes implied by the point estimates also tend to be small. Out of the five different measures of firm growth, only employment growth exhibits a statistically significant and negative relationship with $v_{I\setminus i,t}$.[25]

Kogan et al. (2017) show a negative relation between competitor patenting activities and firm growth, suggesting a creative destruction effect of innovation. Overall, we do not find strong evidence of a relationship between competitor mobile app releases and firm growth. This result highlights the difference between innovative investment and mobile app investment. In particular, a firm's mobile app market investment does not negatively affect competitors in the same industry, suggesting that such investment is not a zero-sum game.

6.3 Sensitivity Tests of Mobile App Value

In our main specification, following Kogan et al. (2017), we set the signal-to-noise ratio δ to 0.0145 and calculate idiosyncratic returns as the difference between firm returns and market returns. In this subsection, we test the robustness of our results to variations in the estimation of the mobile app value. Specifically, we test the sensitivity of two choices: (1) the signal-to-noise ratio and (2) the calculation of idiosyncratic returns.

First, we directly estimate the signal-to-noise ratio using our test sample, and denote the ratio as $\hat{\delta}_{app} \approx 0.024$.[26] Second, we calculate the idiosyncratic return based on the CAPM model to estimate app value.

Table A.9 reports the results. Panels A and B show the results on idiosyncratic volatility and firm growth, respectively. The results confirm that our main findings are robust to

[25] When controlling for a firm's own app value measures, the effect of competitors' app value remains insignificantly different, while the coefficient estimates on the firm's own app value continue to be significantly positive, as in the baseline results.

[26] To estimate δ_{app}, we regress the log squared returns on an app release window indicator variable (I) for the sample of firm-years that have at least one app release, controlling for day of week and firm interacted with year fixed effects. We then use the coefficient estimate on I to back out $\hat{\delta}_{app}$. We also estimate the variance of the measurement error based on $\hat{\delta}_{app}$.

variations in the signal-to-noise ratio and the calculation of idiosyncratic returns. In other words, these choices in estimating mobile app value do not alter the main findings.

6.4 Decomposition

In our sample, about 4% of firms release at least one app in a given year. As a result, our findings can be broken down into two components: (1) the difference between firms that release mobile apps and those that do not (the extensive margin), and (2) the difference between firms that release high-value mobile apps and those that release low-value apps (the intensive margin).

Table A.10 documents the results and shows that our findings are significant for both the extensive and intensive margins. Panels A and B show the results on idiosyncratic volatility and firm growth, respectively. Compared to firms that do not release a mobile app in a given year, those that do experience a decrease in idiosyncratic volatility and an increase in firm growth in the subsequent years. Moreover, within the group of firms that release mobile apps in a given year, those that release high-value apps tend to experience a larger reduction in idiosyncratic volatility and a larger increase in firm growth in the following years, compared to firms that release low-value apps. Overall, our results highlight the significant role of mobile apps in shaping firm risk, growth, and market power.

7 Conclusion

In this paper, we examine the economic value of mobile apps and their impact on firms. We do so by constructing a measure of firms' mobile app value using a unique dataset. Our measure is based on stock returns following the method of Kogan et al. (2017) and intends to capture the private economic value of apps. We show that this estimated economic value of apps strongly and positively correlates with the utility value of these apps, as measured by their future user adoption rates.

Equipped with this measure, we study the relationship between mobile app value and a firm's risk, growth, and market power. Since a crucial component of the app value comes from the data it collects (e.g., Scott Morton et al. (2019), Veldkamp (2023)), we focus on how these apps, by giving access to customer data, enhance firm-specific information environment and affect subsequent growth. We find that the app-value measure is associated with a reduction in firm-specific risks but not systematic risks. Importantly, we find that apps that collect user-linked data have a higher estimated economic value than other apps, and the reduction in firms' idiosyncratic volatility is markedly stronger for apps that collect data. Moreover, firms with poorer initial information environments experience a larger decrease in firm-specific risk following app releases. Consistent with the predictions in Eeckhout and Veldkamp (2022) on the investment-data complementarity channel, we find that firms' mobile app value positively and significantly associates with substantial firm growth and increases in market power. The findings highlight mobile apps as important digital assets in shaping firm information environment and real outcomes.

References

Acemoglu D, Laibson D, List JA. 2014. Equalizing superstars: The internet and the democratization of education. *American Economic Review* **104**: 523–27.

Acemoglu D, Makhdoumi A, Malekian A, Ozdaglar A. 2019. Too much data: Prices and inefficiencies in data markets. Technical report, National Bureau of Economic Research.

Allcott H, Gentzkow M. 2017. Social media and fake news in the 2016 election. *Journal of Economic Perspectives* **31**: 211–36.

Anenberg E, Kung E. 2015. Information technology and product variety in the city: The case of food trucks. *Journal of Urban Economics* **90**: 60–78.

Arnosti N, Beck M, Milgrom P. 2016. Adverse selection and auction design for internet display advertising. *American Economic Review* **106**: 2852–66.

Asquith P, Bruner RF, Mullins Jr DW. 1983. The gains to bidding firms from merger. *Journal of Financial Economics* **11**: 121–139.

Athey S, Calvano E, Gans J. 2013. The impact of the internet on advertising markets for news media. Technical report, National Bureau of Economic Research.

Athey S, Gans JS. 2010. The impact of targeting technology on advertising markets and media competition. *American Economic Review* **100**: 608–13.

Athey S, Mobius M. 2012. The impact of news aggregators on internet news consumption: The case of localization .

Athey S, Stern S. 2000. The impact of information technology on emergency health care outcomes.

Austin DH. 1993. An event-study approach to measuring innovative output: The case of biotechnology. *The American Economic Review* **83**: 253–258.

Bakos Y. 2001. The emerging landscape for retail e-commerce. *Journal of economic perspectives* **15**: 69–80.

Ball R, Brown P. 1968. An empirical evaluation of accounting income numbers. *Journal of Accounting Research* : 159–178.

Beaver WH. 1968. The information content of annual earnings announcements. *Journal of Accounting Research* : 67–92.

Begenau J, Farboodi M, Veldkamp L. 2018. Big data in finance and the growth of large firms. *Journal of Monetary Economics* **97**: 71–87.

Bergemann D, Bonatti A. 2019a. The economics of social data: An introduction .

Bergemann D, Bonatti A. 2019b. Markets for information: An introduction. *Annual Review of Economics* **11**: 85–107.

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

Bloom N, Garicano L, Sadun R, Van Reenen J. 2014. The distinct effects of information technology and communication technology on firm organization. *Management Science* **60**: 2859–2885.

Borenstein S, Saloner G. 2001. Economics and electronic commerce. *Journal of Economic Perspectives* **15**: 3–12.

Boxell L, Gentzkow M, Shapiro JM. 2017. Is the internet causing political polarization? evidence from demographics. Technical report, National Bureau of Economic Research.

Bresnahan TF, Brynjolfsson E, Hitt LM. 2002. Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly Journal of Economics* **117**: 339–376.

Brynjolfsson E, Hu Y, Smith MD. 2003. Consumer surplus in the digital economy: Estimating the value of increased product variety at online booksellers. *Management science* **49**: 1580–1596.

Brynjolfsson E, Smith MD. 2000. Frictionless commerce? a comparison of internet and conventional retailers. *Management science* **46**: 563–585.

Chang R, Da Z. 2022. The dark side of the cloud. *Working Paper* .

Chemmanur TJ, Rajaiya H, Sheng J. 2019. How does soft information affect external firm financing? evidence from online employee ratings. *SSRN Working Paper* : 1–58.

De Loecker J, Eeckhout J, Unger G. 2020. The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics* **135**: 561–644.

Dechow P, Ge W, Schrand C. 2010. Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics* **50**: 344–401.

Eeckhout J, Veldkamp L. 2022. Data and market power. Technical report, National Bureau of Economic Research.

Fama EF, Fisher L, Jensen M, Roll R. 1969. The adjustment of stock prices to new information. *International Economic Review* **10**.

Farboodi M, Mihet R, Philippon T, Veldkamp L. 2019. Big data and firm dynamics. In *AEA papers and proceedings*, volume 109. 38–42.

Farboodi M, Singal D, Veldkamp L, Venkateswaran V. 2022. Valuing financial data. Technical report, National Bureau of Economic Research.

Farboodi M, Veldkamp L. 2021. A growth model of the data economy. *NBER working paper* .

Farboodi M, Veldkamp L. 2022. Data and markets. *Available at SSRN* .

Farre-Mensa J, Hegde D, Ljungqvist A. 2020. What is a patent worth? evidence from the us patent "lottery". *Journal of Finance* **75**: 639–682.

Goldfarb A, Tucker C. 2019. Digital economics. *Journal of Economic Literature* **57**: 3–43.

Hall BH, Jaffe A, Trajtenberg M. 2005. Market value and patent citations. *RAND Journal of Economics* : 16–38.

Hong H, Lim T, Stein JC. 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *Journal of finance* **55**: 265–295.

Huang J. 2018. The customer knows best: The investment value of consumer opinions. *Journal of Financial Economics* **128**: 164–182.

Huang Y, Liu Y, Wu X. 2022. The rise of market power in mobile apps market. *Working Paper* .

Ichihashi S. 2020. Online privacy and information disclosure by consumers. *American Economic Review* **110**: 569–95.

Katona Z, Painter M, Patatoukas PN, Zeng J. 2018. On the capital market consequences of alternative data: Evidence from outer space. In *9th Miami Behavioral Finance Conference*.

Kelly B, Papanikolaou D, Seru A, Taddy M. 2021. Measuring technological innovation over the long run. *American Economic Review: Insights* **3**: 303–20.

Kirpalani R, Philippon T. 2020. Data sharing and market power with two-sided platforms. Technical report, National Bureau of Economic Research.

Kogan L, Papanikolaou D, Schmidt LD, Song J. 2020a. Technological innovation and labor income risk. Technical report, National Bureau of Economic Research.

Kogan L, Papanikolaou D, Seru A, Stoffman N. 2017. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics* **132**: 665–712.

Kogan L, Papanikolaou D, Stoffman N. 2020b. Left behind: Creative destruction, inequality, and the stock market. *Journal of Political Economy* **128**: 855–906.

Kwon SY, Ma Y, Zimmermann K. 2022. 100 years of rising corporate concentration .

Lambrecht A, Tucker CE. 2015. Can big data protect a firm from competition? *Available at SSRN 2705530* .

Lev B. 1989. On the usefulness of earnings and earnings research: Lessons and directions from two decades of empirical research. *Journal of Accounting Research* **27**: 153–192.

Liu Y, Wu X. 2021. Labor links, comovement and predictable returns. *Working Paper* .

Loughran T, Ritter JR. 1995. The new issues puzzle. *The Journal of Finance* **50**: 23–51.

Pakes A. 1985. On patents, r & d, and the stock market rate of return. *Journal of Political Economy* **93**: 390–409.

Post NY. 2017. Americans check their phones 80 times a day: Study. .

Rajgopal S, Srivastava A, Zhao R. 2021. Do digital technology firms earn excess profits? an alternative perspective. *An Alternative Perspective (March 12, 2021)* .

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.

Ritter JR. 1991. The long-run performance of initial public offerings. *The Journal of Finance* **46**: 3–27.

Rossi-Hansberg E, Sarte PD, Trachter N. 2021. Diverging trends in national and local concentration. *NBER Macroeconomics Annual* **35**: 115–150.

Scott Morton F, Bouvier P, Ezrachi A, Jullien B, Katz R, Kimmelman G, Melamed AD, Morgenstern J. 2019. Committee for the study of digital platforms: Market structure and antitrust subcommittee report. *Chicago: Stigler Center for the Study of the Economy and the State, University of Chicago Booth School of Business* **36**.

Sheng J. 2021. Asset pricing in the information age: Employee expectations and stock returns. *Available at SSRN 3321275* .

Travlos NG. 1987. Corporate takeover bids, methods of payment, and bidding firms' stock returns. *The Journal of Finance* **42**: 943–963.

Veldkamp L. 2023. Valuing data as an asset. *Review of Finance* .

Veldkamp L, Chung C. 2019. Data and the aggregate economy. *Journal of Economic Literature* .

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

Table 1: Estimates of Mobile App Value

This table shows the distribution of the following variables across the mobile apps in our sample: the market-adjusted firm returns R on the 3-day window following the mobile app release date, the filtered component of returns $E[\upsilon|R]$ related to the value of mobile app, the filtered dollar value of ξ, and the forward average weekly number of downloads D. Market-adjusted returns are computed as the difference between the firm return minus the return of the CRSP value-weighted index. The sample contains 7,844 mobile apps.

	R (%)	$E[\upsilon\|R]$ (%)	ξ (mil)	D
Mean	0.13	0.29	119.76	4022.02
SD	3.78	0.16	308.54	17164.62
Percentiles				
P1	-8.89	0.11	0.09	6.70
P5	-4.78	0.13	0.81	12.15
P10	-3.30	0.15	2.41	19.14
P25	-1.39	0.18	6.85	55.53
P50	0.00	0.26	24.31	237.72
P75	1.43	0.36	103.17	1331.79
P90	3.29	0.48	317.51	7512.37
P95	5.14	0.61	502.36	18294.64
P99	12.29	0.83	1326.72	76119.15

Table 2: Summary Statistics

This table presents descriptive statistics for firm-level characteristics. v^{sm} and v^{dw} are firm's mobile app-value measures, where v^{sm} is defined in equation 1 using stock market reaction, and v^{dw} is defined in equation 2 using app downloads. We also report the natural logarithm of firm size (market capitalization in the construction of v^{sm}), vol (idiosyncratic volatility in the construction of v^{sm}), and the logged growth rate in firm idiosyncratic volatility ($\Delta idiovol_{ff5}$ calculated based on Fama-French 5-factor models), firm sales ($\Delta sale$ using COMPUSTAT sale), firm employment (Δemp using COMPUSTAT emp), firm EBIT ($\Delta ebit$ using COMPUSTAT ebit), firm EBITDA ($\Delta ebitda$ using COMPUSTAT ebitda), and firm asset (Δat using COMPUSTAT at). All variables are winsorized at the 1% level using annual breakpoints.

	Mean	SD	p1	p25	p50	p75	p99
v^{sm} (%)	0.04	0.24	0.00	0.00	0.00	0.00	1.39
v^{dw} (%)	0.00	0.01	0.00	0.00	0.00	0.00	0.01
$\log(size)$	6.45	2.17	1.96	4.88	6.41	7.96	11.46
vol	0.05	0.04	0.01	0.03	0.04	0.07	0.20
$\Delta idiovol_{ff5}$	-0.02	0.38	-0.91	-0.26	-0.03	0.19	0.98
$\Delta sale$	0.06	0.36	-1.19	-0.04	0.05	0.15	1.39
Δemp	0.03	0.23	-0.77	-0.04	0.02	0.10	0.82
$\Delta ebit$	0.07	0.55	-1.83	-0.09	0.07	0.25	1.90
$\Delta ebitda$	0.07	0.48	-1.56	-0.07	0.07	0.22	1.62
Δat	0.06	0.28	-0.69	-0.04	0.04	0.14	1.09

Table 3: Forward Download and Mobile App Value

This table presents the results from estimating equation 3 relating the estimated mobile app value to the forward average weekly download. The dollar value of an app is constructed as described in Section 2.2. Depending on the specification we include firm size, firm idiosyncratic volatility, time fixed effect, and time-app category fixed effect. We cluster the standard errors at the mobile app release year and report in parentheses. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(D_j)$	0.169***	0.041***	0.018***	0.144***	0.027***	0.015***	0.148***	0.022***	0.012***
	(0.020)	(0.008)	(0.005)	(0.023)	(0.005)	(0.004)	(0.016)	(0.003)	(0.002)
Firm Size	N	Y	Y	N	Y	Y	N	Y	Y
Volatility	N	N	Y	N	N	Y	N	N	Y
Time FE	N	N	N	Y	Y	Y	N	N	N
Time*Category FE	N	N	N	N	N	N	Y	Y	Y
Num of Obs	7,844	7,844	7,844	7,844	7,844	7,844	7,353	7,353	7,353
R^2	0.035	0.896	0.921	0.097	0.908	0.925	0.322	0.938	0.953

Table 4: Mobile App Value and Idiosyncratic Volatility

This table reports regression estimates of model 4 for firm-specific idiosyncratic volatility. We regress changes in firm idiosyncratic volatility on firm mobile app value, where firm app value is measured as in equation 1 using stock market reaction. Firm-level idiosyncratic volatility is calculated based on one of the Fama-French 3-factor, Fama-French 3-factor plus momentum factor, the Fama-French 5-factor, and the Fama-French 5-factor plus momentum factor models. The table presents results for horizons of one to five years. Controls include lagged logged size, lagged volatility, and time & industry fixed effects. Standard errors are clustered by firm and reported in parentheses. Firm mobile app-value measures are normalized to have mean zero and standard deviation of one. Dependent variables are multiplied by 100. Each entry represents a separate regression. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	FF3	FF3 + Mom	FF5	FF5 + Mom
+1	-0.528***	-0.514***	-0.531***	-0.520***
	(0.098)	(0.097)	(0.098)	(0.097)
+2	-0.944***	-0.952***	-0.949***	-0.956***
	(0.122)	(0.122)	(0.123)	(0.122)
+3	-1.420***	-1.423***	-1.415***	-1.421***
	(0.163)	(0.162)	(0.163)	(0.162)
+4	-1.544***	-1.539***	-1.537***	-1.537***
	(0.190)	(0.190)	(0.192)	(0.192)
+5	-1.771***	-1.787***	-1.760***	-1.782***
	(0.231)	(0.232)	(0.234)	(0.234)

Table 5: Download-Weighted Mobile App Value and Idiosyncratic Volatility

This table reports regression estimates of model 4 for firm-specific idiosyncratic volatility. We regress changes in firm idiosyncratic volatility on firm mobile app value, measured by v^{sm} or v^{dw}. v^{sm} is defined in equation 1 using stock market reaction, and v^{dw} is defined in equation 2 using app downloads. Panel A only includes v^{dw} and Panel B includes both v^{sm} and v^{dw}. Firm-level idiosyncratic volatility is calculated based on one of the Fama-French 3-factor, Fama-French 3-factor plus momentum factor, the Fama-French 5-factor, and the Fama-French 5-factor plus momentum factor models. The table presents results for horizons of one to five years. Controls include lagged logged size, lagged volatility, and time & industry fixed effects. Standard errors are clustered by firm and reported in parentheses. Firm mobile app-value measures are normalized to have mean zero and standard deviation of one. Dependent variables are multiplied by 100. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

		(1)	(2)	(3)	(4)
Panel A		FF3	FF3 + Mom	FF5	FF5 + Mom
+1	v^{dw}	-0.188	-0.188	-0.194*	-0.192*
		(0.116)	(0.115)	(0.116)	(0.116)
+2	v^{dw}	-0.291**	-0.288**	-0.310**	-0.308**
		(0.145)	(0.144)	(0.145)	(0.144)
+3	v^{dw}	-0.657***	-0.651***	-0.661***	-0.655***
		(0.160)	(0.159)	(0.160)	(0.159)
+4	v^{dw}	-0.976***	-0.979***	-0.980***	-0.985***
		(0.159)	(0.160)	(0.160)	(0.160)
+5	v^{dw}	-0.885***	-0.900***	-0.882***	-0.899***
		(0.194)	(0.193)	(0.194)	(0.193)
Panel B		FF3	FF3 + Mom	FF5	FF5 + Mom
+1	v^{sm}	-0.575***	-0.557***	-0.575***	-0.562***
		(0.121)	(0.120)	(0.121)	(0.121)
	v^{dw}	0.091	0.083	0.086	0.081
		(0.140)	(0.140)	(0.141)	(0.141)
+2	v^{sm}	-1.057***	-1.069***	-1.050***	-1.061***
		(0.156)	(0.155)	(0.157)	(0.156)
	v^{dw}	0.217	0.226	0.194	0.202
		(0.171)	(0.171)	(0.172)	(0.171)
+3	v^{sm}	-1.429***	-1.438***	-1.419***	-1.432***
		(0.187)	(0.186)	(0.188)	(0.187)
	v^{dw}	0.016	0.027	0.008	0.019
		(0.178)	(0.176)	(0.178)	(0.177)
+4	v^{sm}	-1.330***	-1.321***	-1.317***	-1.313***
		(0.211)	(0.211)	(0.214)	(0.213)
	v^{dw}	-0.362**	-0.369**	-0.373**	-0.379**
		(0.174)	(0.174)	(0.174)	(0.174)
+5	v^{sm}	-1.688***	-1.697***	-1.674***	-1.690***
		(0.248)	(0.248)	(0.251)	(0.251)
	v^{dw}	-0.135	-0.146	-0.138	-0.148
		(0.204)	(0.202)	(0.204)	(0.202)

Table 6: Data Collection and Idiosyncratic Volatility

This table reports results related to app data collection and firm idiosyncratic volatility. Pane A reports summary statistics of firm mobile app value for apps with or without data collection, where firm mobile app value is measured by v^{sm} as defined in equation 1. Panel B reports regression estimates of model 5, where we regresses changes in firm idiosyncratic volatility on indicator variables for mobile apps that collect data and for other mobile apps, respectively. The panel presents results for horizons of one to five years. Firm-level idiosyncratic volatility is calculated based on one of the Fama-French 3-factor, Fama-French 3-factor plus momentum factor, the Fama-French 5-factor, and the Fama-French 5-factor plus momentum factor models. Controls include lagged logged size, lagged volatility, and time & industry fixed effects. Standard errors are clustered by firm and reported in parentheses. Dependent variables are multiplied by 100. Each entry represents a separate regression. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Summary Statistics

	Apps collect data	Other apps	Diff in Mean
Mean (v^{sm})	4.13	2.12	2.01***
Std. Dev (v^{sm})	4.54	3.22	

Panel B		(1)	(2)	(3)	(4)
		FF3	FF3 + Mom	FF5	FF5 + Mom
+1	β^{Data}	-1.560*	-1.631*	-1.616*	-1.653*
		(0.893)	(0.894)	(0.891)	(0.892)
	β^{Other}	-1.081*	-1.094*	-1.189**	-1.190**
		(0.599)	(0.597)	(0.603)	(0.602)
+2	β^{Data}	-3.918***	-4.061***	-4.030***	-4.128***
		(1.099)	(1.097)	(1.099)	(1.096)
	β^{Other}	-1.855**	-1.916***	-2.072***	-2.100***
		(0.743)	(0.740)	(0.740)	(0.739)
+3	β^{Data}	-5.264***	-5.320***	-5.453***	-5.495***
		(1.384)	(1.379)	(1.382)	(1.375)
	β^{Other}	-2.798***	-2.896***	-3.014***	-3.091***
		(0.901)	(0.894)	(0.899)	(0.896)
+4	β^{Data}	-7.133***	-7.218***	-7.293***	-7.387***
		(1.590)	(1.589)	(1.597)	(1.595)
	β^{Other}	-1.878*	-1.931*	-2.118**	-2.168**
		(1.032)	(1.029)	(1.033)	(1.032)
+5	β^{Data}	-6.876***	-7.001***	-7.094***	-7.181***
		(1.856)	(1.853)	(1.860)	(1.853)
	β^{Other}	-2.622**	-2.765**	-2.686**	-2.849**
		(1.207)	(1.209)	(1.207)	(1.209)

Table 7: Mobile App Value, Idiosyncratic Volatility, and Information Environment

This table reports results of the relation between firm app value and changes in idiosyncratic volatility across subsamples based on firm size in Panel A and the number of analysts following in Panel B, respectively. Firm app value v^{sm} is measured as in equation 1 using stock market reaction. Firm-level idiosyncratic volatility is calculated based on one of the Fama-French 3-factor, Fama-French 3-factor plus momentum factor, the Fama-French 5-factor, and the Fama-French 5-factor plus momentum factor models. $Large$ is an indicator variable that equals one if a firm's lagged size is above the sample median, and zero otherwise. $High$ is an indicator variable that equals one if a firm's lagged number of analysts following is above the sample median, and zero otherwise. The table presents coefficient estimates of v^{sm} and the interaction term of v^{sm} and the subsample variable for the three-year horizon. Controls include lagged logged size, lagged volatility, and time & industry fixed effects. Standard errors are clustered by firm and reported in parentheses. Firm mobile app-value measures are normalized to have mean zero and standard deviation of one. Dependent variables are multiplied by 100. Each row represents a separate regression. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A	Size	
	v^{sm}	$v^{sm} \times Large$
FF3	-3.172***	1.887***
	(0.717)	(0.731)
FF3 + Mom	-3.127***	1.836**
	(0.713)	(0.726)
FF5	-3.169***	1.890**
	(0.723)	(0.737)
FF5 + Mom	-3.136***	1.848**
	(0.718)	(0.732)

Panel B	Analyst Coverage	
	v^{sm}	$v^{sm} \times High$
FF3	-2.768***	1.573***
	(0.498)	(0.520)
FF3 + Mom	-2.768***	1.571***
	(0.490)	(0.511)
FF5	-2.760***	1.567***
	(0.503)	(0.525)
FF5 + Mom	-2.768***	1.572***
	(0.494)	(0.516)

Table 8: Mobile App Value and Firm Growth

This table reports regression estimates of model 6 for firm sales, employment, EBIT, EIBTDA, and asset. We regress future firm growth on firm mobile app value, where growth is measured by one of firm sales (COMPUSTAT sale), firm employment (COMPUSTAT emp), firm EBIT (COMPUSTAT ebit), firm EBITDA (COMPUSTAT ebitda), and firm asset (COMPUSTAT at), and firm app value is measured as in equation 1 using stock market reaction. The table presents results for horizons of one to five years. Controls include lagged logged size, lagged volatility, and time & industry fixed effects. Standard errors are clustered by firm and reported in parentheses. Firm mobile app-value measures are normalized to have mean zero and standard deviation of one. Each entry represents a separate regression. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) SALE	(2) EMP	(3) EBIT	(4) EBITDA	(5) AT
+1	0.009***	0.007***	0.010***	0.010***	0.010***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
+2	0.017***	0.014***	0.015***	0.018***	0.020***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)
+3	0.025***	0.021***	0.021***	0.021***	0.030***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
+4	0.033***	0.027***	0.029***	0.031***	0.038***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
+5	0.040***	0.032***	0.032***	0.038***	0.047***
	(0.006)	(0.006)	(0.008)	(0.007)	(0.006)

Table 9: Download-Weighted Mobile App Value and Firm Growth

This table reports regression estimates of model 6 for firm sales, employment, EBIT, EIBTDA, and asset. We regress future firm growth on firm mobile app value, where growth is measured by one of firm sales (COMPUSTAT sale), firm employment (COMPUSTAT emp), firm EBIT (COMPUSTAT ebit), firm EBITDA (COMPUSTAT ebitda), and firm asset (COMPUSTAT at), and firm app value is measured by v^{sm} or v^{dw}. v^{sm} is defined in equation 1 using stock market reaction, and v^{dw} is defined in equation 2 using app downloads. Panel A only includes v^{dw} and Panel B includes both v^{sm} and v^{dw}. The table presents results for horizons of one to five years. Controls include lagged logged size, lagged volatility, and time & industry fixed effects. Standard errors are clustered by firm and reported in parentheses. Firm mobile app-value measures are normalized to have mean zero and standard deviation of one. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A		(1)	(2)	(3)	(4)	(5)
		SALE	EMP	EBIT	EBITDA	AT
+1	v^{dw}	0.006***	0.005***	0.004	0.006***	0.007***
		(0.001)	(0.001)	(0.003)	(0.002)	(0.001)
+2	v^{dw}	0.011***	0.010***	0.007**	0.012***	0.013***
		(0.002)	(0.002)	(0.004)	(0.003)	(0.002)
+3	v^{dw}	0.016***	0.013***	0.014***	0.016***	0.017***
		(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
+4	v^{dw}	0.020***	0.015***	0.019***	0.016***	0.021***
		(0.004)	(0.004)	(0.005)	(0.005)	(0.003)
+5	v^{dw}	0.022***	0.020***	0.019***	0.022***	0.026***
		(0.004)	(0.004)	(0.006)	(0.005)	(0.004)
Panel B		SALE	EMP	EBIT	EBITDA	AT
+1	v^{sm}	0.007***	0.006***	0.010***	0.009***	0.009***
		(0.001)	(0.001)	(0.003)	(0.003)	(0.001)
	v^{dw}	0.003*	0.003**	-0.000	0.002	0.003*
		(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
+2	v^{sm}	0.015***	0.012***	0.015***	0.016***	0.018***
		(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
	v^{dw}	0.004*	0.004*	0.000	0.004	0.004*
		(0.002)	(0.002)	(0.004)	(0.003)	(0.002)
+3	v^{sm}	0.022***	0.019***	0.018***	0.017***	0.028***
		(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
	v^{dw}	0.005*	0.004	0.006	0.008*	0.004
		(0.003)	(0.003)	(0.005)	(0.004)	(0.003)
+4	v^{sm}	0.030***	0.024***	0.023***	0.029***	0.036***
		(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
	v^{dw}	0.006*	0.004	0.009**	0.003	0.005
		(0.003)	(0.003)	(0.005)	(0.005)	(0.003)
+5	v^{sm}	0.037***	0.028***	0.028***	0.034***	0.043***
		(0.006)	(0.006)	(0.008)	(0.008)	(0.006)
	v^{dw}	0.006	0.007*	0.008	0.007	0.006*
		(0.004)	(0.004)	(0.005)	(0.005)	(0.004)

Table 10: Mobile App Value and Market Share

This table reports regression estimates of model 6 for firm market share. We regress changes in firm market share on firm mobile app value, where firm market share is measured by either share of assets (MS^{at}) or share of sales (MS^{sale}) in the industry, and firm app value is measured by v^{sm} or v^{dw}. v^{sm} is defined in equation 1 using stock market reaction, and v^{dw} is defined in equation 2 using app downloads. Panel A uses MS^{at} and Panel B uses MS^{sale}. Each Panel has three model specifications: (1) with only v^{sm}, (2) with only v^{dw}, and (3) with both v^{sm} and v^{dw}. The table presents results for horizons of one to five years. Controls include lagged logged size, lagged volatility, and time & industry fixed effects. Standard errors are clustered by firm and reported in parentheses. Firm mobile app-value measures are normalized to have mean zero and standard deviation of one. Dependent variables are multiplied by 100. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A		+1	+2	+3	+4	+5
				MS^{at}		
(1)	v^{sm}	0.890***	1.637***	2.571***	3.285***	4.024***
		(0.137)	(0.251)	(0.373)	(0.476)	(0.568)
(2)	v^{dw}	0.648***	1.017***	1.417***	1.876***	2.136***
		(0.135)	(0.233)	(0.316)	(0.371)	(0.409)
(3)	v^{sm}	0.742***	1.476***	2.412***	2.999***	3.753***
		(0.145)	(0.258)	(0.371)	(0.478)	(0.582)
	v^{dw}	0.289**	0.311	0.287	0.500	0.452
		(0.142)	(0.236)	(0.296)	(0.341)	(0.370)

Panel B		+1	+2	+3	+4	+5
				MS^{sale}		
(1)	v^{sm}	0.751***	1.397***	2.083***	2.808***	3.436***
		(0.138)	(0.246)	(0.370)	(0.475)	(0.566)
(2)	v^{dw}	0.557***	0.911***	1.240***	1.628***	1.777***
		(0.145)	(0.238)	(0.304)	(0.372)	(0.426)
(3)	v^{sm}	0.617***	1.228***	1.884***	2.542***	3.239***
		(0.151)	(0.261)	(0.386)	(0.482)	(0.574)
	v^{dw}	0.258	0.325	0.360	0.464	0.327
		(0.160)	(0.250)	(0.302)	(0.349)	(0.395)

Table 11: Mobile App Value and Cash-Flow Volatility

This table reports regression estimates of model 7 for firm cash-flow volatility. We regress changes in cash-flow volatility on firm mobile app value, where firm cash flow volatility is measured as the standard deviation of its quarterly cash flows using a three-year trailing window, and firm app value is measured by v^{sm} or v^{dw}. Cash flow is the operating income before depreciation (COMPUSTAT oiadpq) scaled by either lagged assets (CF^{at}) or lagged sales (CF^{sale}) . v^{sm} is defined in equation 1 using stock market reaction, and v^{dw} is defined in equation 2 using app downloads. Panel A uses CF^{at} and Panel B uses CF^{sale}. Each Panel has three model specifications: (1) with only v^{sm}, (2) with only v^{dw}, and (3) with both v^{sm} and v^{dw}. The table presents results for horizons of one to five years. Controls include lagged logged size, lagged volatility, and time & industry fixed effects. Standard errors are clustered by firm and reported in parentheses. Firm mobile app-value measures are normalized to have mean zero and standard deviation of one. Dependent variables are multiplied by 100. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A		+3	+4	+5
			$sd\left(CF^{at}\right)$	
(1)	v^{sm}	-0.937**	-1.280***	-1.851***
		(0.380)	(0.485)	(0.573)
(2)	v^{dw}	-0.218	-0.660*	-0.958**
		(0.357)	(0.384)	(0.424)
(3)	v^{sm}	-1.114***	-1.256**	-1.800***
		(0.417)	(0.531)	(0.617)
	v^{dw}	0.340	-0.041	-0.088
		(0.383)	(0.401)	(0.425)

Panel B		+3	+4	+5
			$sd\left(CF^{sale}\right)$	
(1)	v^{sm}	-0.862**	-1.291***	-1.942***
		(0.393)	(0.499)	(0.595)
(2)	v^{dw}	-0.150	-0.477	-0.899**
		(0.345)	(0.390)	(0.448)
(3)	v^{sm}	-1.048**	-1.395***	-1.953***
		(0.421)	(0.522)	(0.611)
	v^{dw}	0.355	0.183	0.019
		(0.358)	(0.381)	(0.419)

Figure 1: Cumulative Number of Mobile App Released

This graph plots the cumulative numbers of mobile apps over time in the sample. The sample spans 2008 to 2021.

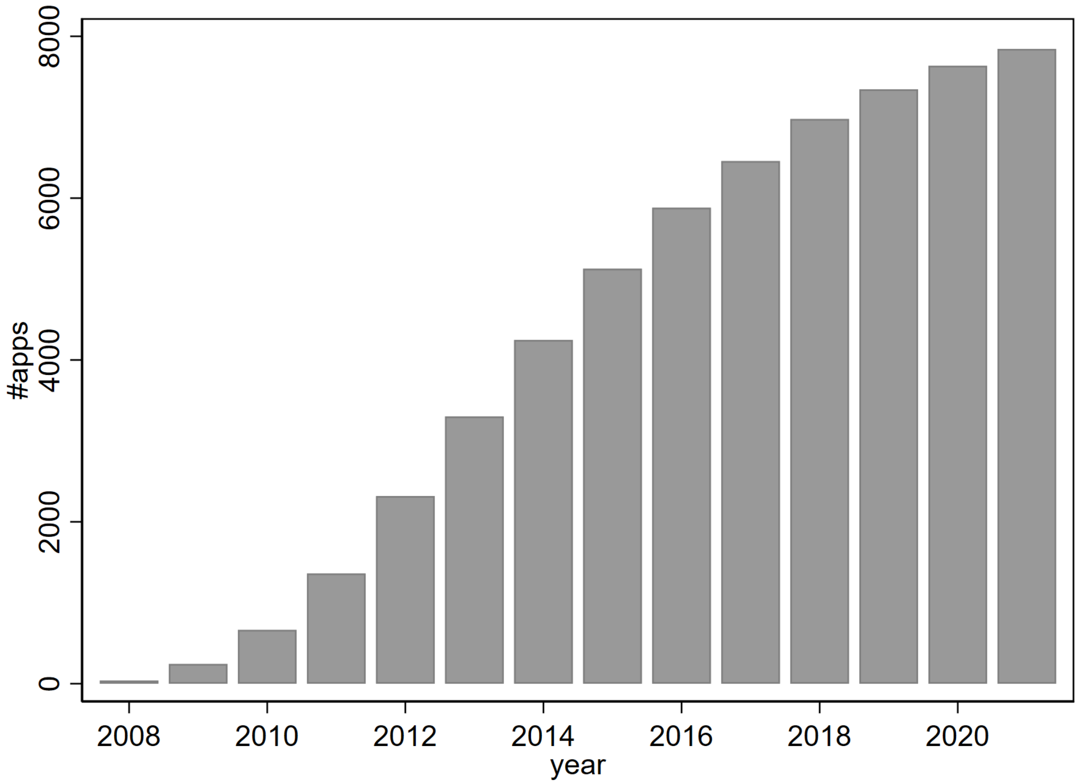
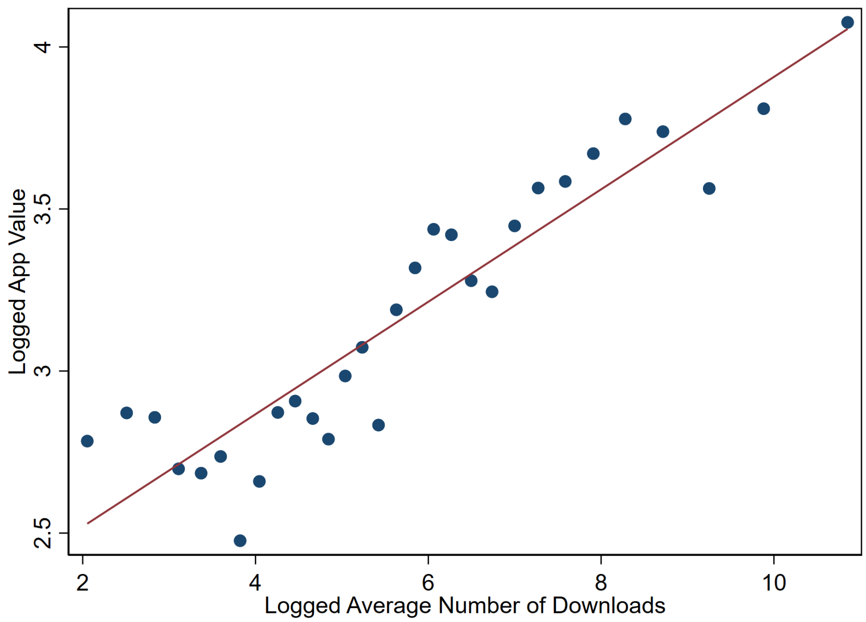
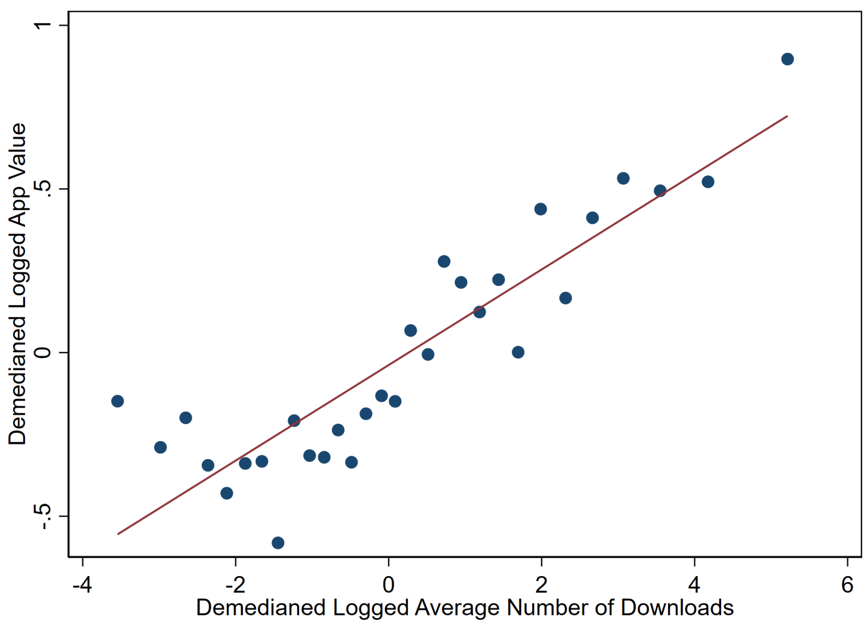


Figure 2: Relation between Mobile App Value and Future Average Download

This figure plots the logged app value against the forward logged average number of downloads for the apps. Panel A is based on the raw numbers and Panel B adjusts for the yearly sample median. The sample is grouped into 30 dots and each dot represents multiple underlying observations. The sample spans from 2008 to 2021.





Appendix for Online Publication

A. Tables

Table A.1: Summary Statistics of Estimated App Value by App Category

This table presents descriptive statistics of the estimated mobile app value by iOS app category. The sample requires nonmissing category information and at least 10 apps in the category. The dollar value of an app is constructed as described in Section 2.2.

Category	Name	mean	median	std	#apps
6000	Business	189.47	44.34	432.64	1098
6001	Weather	21.09	2.85	102.53	233
6002	Utilities	172.40	39.06	329.76	331
6003	Travel	68.67	25.07	116.68	193
6004	Sports	68.64	20.47	83.88	162
6005	Social Networking	192.82	18.66	432.73	126
6006	Reference	82.20	28.87	165.76	68
6007	Productivity	206.35	48.87	354.55	311
6008	Photo & Video	209.75	24.89	449.21	182
6009	News	41.07	1.78	126.93	403
6010	Navigation	104.16	18.48	212.62	79
6011	Music	139.58	8.03	424.32	92
6012	Lifestyle	141.72	33.42	453.08	288
6013	Health & Fitness	204.33	34.67	584.26	204
6014	Games	63.94	15.75	175.87	1584
6015	Finance	109.41	35.86	217.66	387
6016	Entertainment	163.77	52.02	389.17	659
6017	Education	100.98	15.35	250.81	269
6018	Books	74.31	52.68	98.55	85
6020	Medical	95.64	37.45	155.63	179
6022	Catalogs	106.56	33.15	132.11	13
6023	Food & Drink	85.80	45.27	119.81	170
6024	Shopping	89.10	27.43	171.55	247

Table A.2: Active Users and Mobile App Value

This table presents the results from estimating equation 3 relating the estimated mobile app value to the forward average weekly active users. For active users, only apps with available data are included. The dollar value of an app is constructed as described in Section 2.2. Depending on the specification, we include firms size, firm idiosyncratic volatility, time fixed effect, and time-app category fixed effect. We cluster the standard errors at the mobile app release year and report standard errors in parentheses. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Active Users	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(A_j)$	0.105***	0.030***	0.013***	0.083***	0.013***	0.006***	0.079***	0.012***	0.006**
	(0.011)	(0.005)	(0.003)	(0.014)	(0.003)	(0.002)	(0.018)	(0.003)	(0.002)
Firm Size	N	Y	Y	N	Y	Y	N	Y	Y
Volatility	N	N	Y	N	N	Y	N	N	Y
Time FE	N	N	N	Y	Y	Y	N	N	N
Time-Category FE	N	N	N	N	N	N	Y	Y	Y
Num of Obs	4,821	4,821	4,821	4,821	4,821	4,821	4,455	4,455	4,455
R^2	0.023	0.885	0.909	0.081	0.897	0.915	0.303	0.934	0.950

Table A.3: Mobile App Value and Idiosyncratic Volatility – Robustness

This table reports regression outputs for firm-specific idiosyncratic volatility. We regress changes in firm-specific idiosyncratic volatility on firm mobile app value, measured as in equation 1 using stock market reaction. Firm-level idiosyncratic volatility is calculated based on one of the Fama-French 3-factor, Fama-French 3-factor plus momentum factor, the Fama-French 5-factor, and the Fama-French 5-factor plus momentum factor models. Controls include lagged logged size, lagged volatility, and time & industry fixed effects, as well as capital investment rate, R&D rate, SG&A rate, Tobin's Q, and the Kogan et al. (2017) patent value measure scaled by lagged total assets. Standard errors are clustered by firm and reported in parentheses. Firm mobile app-value measures are normalized to have mean zero and standard deviation of one. Dependent variables are multiplied by 100. Each entry represents a separate regression. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	FF3	FF3 + Mom	FF5	FF5 + Mom
+1	-0.381*	-0.366*	-0.382*	-0.370*
	(0.203)	(0.198)	(0.198)	(0.196)
+2	-0.820***	-0.824***	-0.827***	-0.831***
	(0.226)	(0.218)	(0.212)	(0.207)
+3	-1.215***	-1.217***	-1.216***	-1.220***
	(0.297)	(0.290)	(0.292)	(0.287)
+4	-1.327***	-1.320***	-1.326***	-1.324***
	(0.290)	(0.287)	(0.288)	(0.286)
+5	-1.477***	-1.493***	-1.473***	-1.494***
	(0.312)	(0.323)	(0.315)	(0.325)

Table A.4: Mobile App Value and Synchronicity

This table reports regression outputs for stock market informativeness. We regress changes in stock market informativeness on firm mobile app value, where stock market informativeness is measured by firms' synchronicity and mobile app value is measured as in equation 1 using stock market reaction. Firm-level synchronicity is calculated based on one of the Fama-French 3-factor, Fama-French 3-factor plus momentum factor, the Fama-French 5-factor, and the Fama-French 5-factor plus momentum factor models. Controls include lagged logged size, lagged volatility, and time & industry fixed effects. Standard errors are clustered by firm and reported in parentheses. Each entry represents a separate regression. Firm mobile app-value measures are normalized to have mean zero and standard deviation of one. Dependent variables are multiplied by 100. Each entry represents a separate regression. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	FF3	FF3 + Mom	FF5	FF5 + Mom
+1	0.963***	0.818***	0.845***	0.718***
	(0.190)	(0.181)	(0.180)	(0.171)
+2	1.790***	1.629***	1.513***	1.426***
	(0.267)	(0.254)	(0.244)	(0.233)
+3	1.983***	1.737***	1.543***	1.436***
	(0.357)	(0.337)	(0.328)	(0.312)
+4	2.667***	2.358***	2.213***	2.048***
	(0.391)	(0.375)	(0.356)	(0.345)
+5	3.381***	3.083***	2.771***	2.647***
	(0.465)	(0.444)	(0.416)	(0.403)

Table A.5: Mobile App Value and Systematic Risk

This table reports regression outputs for firms' systematic risk. We regress changes in systematic risk of firms on firm mobile app value, where systematic risk is measured by firm market beta based on Fama-French 3-factor model and mobile app value is measured as in equation 1 using stock market reaction. Controls include lagged logged size, lagged volatility, and time & industry fixed effects. Standard errors are clustered by firm and reported in parentheses. There are three model specifications: (1) with only v^{sm}, (2) with only v^{dw}, and (3) with both v^{sm} and v^{dw}. Firm mobile app-value measures are normalized to have mean zero and standard deviation of one. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

		+1	+2	+3	+4	+5
				β^{CAPM}		
(1)	v^{sm}	-0.000	0.003	0.001	-0.002	0.001
		(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
(2)	v^{dw}	0.001	0.003	0.002	-0.000	0.001
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
(3)	v^{sm}	-0.001	0.002	-0.001	-0.003	0.000
		(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
	v^{dw}	0.002	0.002	0.002	0.001	0.001
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)

Table A.6: Mobile App Value and Firm Growth – Robustness

This table reports regression estimates of model 6 for firm sales, employment, EBIT, EIBTDA, and asset. We regress future firm growth on firm mobile app value, where growth is measured by one of firm sales (COMPUSTAT sale), firm employment (COMPUSTAT emp), firm EBIT (COMPUSTAT ebit), firm EBITDA (COMPUSTAT ebitda), and firm asset (COMPUSTAT at), and firm app value is measured as in equation 1 using stock market reaction. The table presents results for horizons of one to five years. Controls include lagged logged size, lagged volatility, and time & industry fixed effects, as well as capital investment rate, R&D rate, SG&A rate, Tobin's Q, and the Kogan et al. (2017) patent value measure scaled by lagged total assets. Standard errors are clustered by firm and reported in parentheses. Firm mobile app-value measures are normalized to have mean zero and standard deviation of one. Each entry represents a separate regression. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) SALE	(2) EMP	(3) EBIT	(4) EBITDA	(5) AT
+1	0.004***	0.003*	0.005*	0.005*	0.003**
	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)
+2	0.009***	0.007**	0.010***	0.012***	0.009***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
+3	0.013***	0.011**	0.015***	0.013**	0.016***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
+4	0.018***	0.015***	0.022***	0.020***	0.020***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
+5	0.023***	0.019***	0.025***	0.026***	0.026***
	(0.005)	(0.006)	(0.007)	(0.006)	(0.005)

Table A.7: Mobile App Value and Market Share – Robustness

This table reports regression estimates of model 6 for firm market share. We regress changes in firm market share on firm mobile app value, where firm market share is measured by either share of assets (MS^{at}) or share of sales (MS^{sale}) in the industry, and firm app value is measured by v^{sm} as defined in equation 1. Panel A uses MS^{at} and Panel B uses MS^{sale}. The table presents results for horizons of one to five years. Controls include lagged logged size, lagged volatility, and time & industry fixed effects, as well as capital investment rate, R&D rate, SG&A rate, Tobin's Q, and the Kogan et al. (2017) patent value measure scaled by lagged total assets. Standard errors are clustered by firm and reported in parentheses. Firm mobile app-value measures are normalized to have mean zero and standard deviation of one. Dependent variables are multiplied by 100. Each entry represents a separate regression. Each entry represents a separate regression. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A	+1	+2	+3	+4	+5
			MS^{at}		
v^{sm}	0.290	0.640*	1.216**	1.583**	2.123***
	(0.178)	(0.317)	(0.409)	(0.573)	(0.644)

Panel B	+1	+2	+3	+4	+5
			MS^{sale}		
v^{sm}	0.326**	0.615**	0.954**	1.344**	1.866***
	(0.129)	(0.234)	(0.341)	(0.497)	(0.571)

Table A.8: Competitor Mobile App Value and Firm Growth

This table reports regression estimates of model 9 for firm sales, employment, EBIT, EIBTDA, and asset. We regress future firm growth on the mobile app value by the firm's competitors, where growth is measured by one of firm sales (COMPUSTAT sale), firm employment (COMPUSTAT emp), firm EBIT (COMPUSTAT ebit), firm EBITDA (COMPUSTAT ebitda), and firm asset (COMPUSTAT at), and competitors' app value is measured as in equation 8 using stock market reaction. The table presents results for horizons of one to five years. Controls include lagged logged size, lagged volatility, and time & industry fixed effects. Standard errors are clustered by firm and reported in parentheses. Competitors' mobile app-value measures are normalized to have mean zero and standard deviation of one. Each entry represents a separate regression. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	SALE	EMP	EBIT	EBITDA	AT
+1	-0.005	-0.005*	-0.003	-0.010	-0.002
	(0.003)	(0.002)	(0.006)	(0.007)	(0.003)
+2	-0.003	-0.009**	-0.004	0.001	-0.006
	(0.005)	(0.004)	(0.009)	(0.010)	(0.007)
+3	-0.007	-0.012	0.010	0.001	-0.009
	(0.009)	(0.007)	(0.013)	(0.017)	(0.009)
+4	-0.003	-0.017	0.008	0.002	-0.008
	(0.012)	(0.010)	(0.015)	(0.017)	(0.010)
+5	0.003	-0.021	0.007	0.002	0.002
	(0.015)	(0.013)	(0.015)	(0.015)	(0.012)

Table A.9: Sensitivity Tests: Alternative Mobile App Value Estimates

This table reports the sensitivity tests of the main results for idiosyncratic volatility and firm growth using alternative estimations of mobile app value. Panel A reports results for idiosyncratic volatility and Panel B reports results for firm growth. The specifications are the same as the baseline analyses. The first sensitivity test changes the signal-to-noise ratio to 0.024, estimated using the app sample, to reconstruct the mobile app value. The second sensitivity test uses CAPM adjusted excess returns for app value estimates. Controls include lagged logged size, lagged volatility, and time & industry fixed effects. Standard errors are clustered by firm and reported in parentheses. Dependent variables in Panel A are multiplied by 100. Each entry represents a separate regression. Each entry represents a separate regression. Firm mobile app-value measures are normalized to have mean zero and standard deviation of one. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Idiosyncratic Volatility				
	(1)	(2)	(3)	(4)
$\delta = 0.024$	FF3	FF3 + Mom	FF5	FF5 + Mom
+1	-0.525***	-0.513***	-0.529***	-0.519***
	(0.098)	(0.098)	(0.098)	(0.098)
+2	-0.945***	-0.953***	-0.951***	-0.957***
	(0.122)	(0.122)	(0.123)	(0.122)
+3	-1.416***	-1.419***	-1.411***	-1.417***
	(0.163)	(0.162)	(0.163)	(0.162)
+4	-1.544***	-1.539***	-1.537***	-1.536***
	(0.189)	(0.189)	(0.192)	(0.192)
+5	-1.769***	-1.785***	-1.758***	-1.779***
	(0.231)	(0.231)	(0.233)	(0.234)
	(1)	(2)	(3)	(4)
CAPM-adj	FF3	FF3 + Mom	FF5	FF5 + Mom
+1	-0.478***	-0.464***	-0.481***	-0.470***
	(0.095)	(0.095)	(0.095)	(0.095)
+2	-0.891***	-0.898***	-0.896***	-0.902***
	(0.120)	(0.120)	(0.120)	(0.120)
+3	-1.395***	-1.397***	-1.390***	-1.395***
	(0.161)	(0.160)	(0.161)	(0.161)
+4	-1.495***	-1.490***	-1.487***	-1.488***
	(0.187)	(0.187)	(0.189)	(0.189)
+5	-1.727***	-1.744***	-1.715***	-1.737***
	(0.232)	(0.232)	(0.234)	(0.234)

Panel B. Firm Growth					
	(1)	(2)	(3)	(4)	(5)
$\delta = 0.024$	SALE	EMP	EBIT	EBITDA	AT
+1	0.009***	0.007***	0.010***	0.010***	0.010***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
+2	0.017***	0.014***	0.015***	0.018***	0.020***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)
+3	0.025***	0.021***	0.021***	0.021***	0.030***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
+4	0.034***	0.027***	0.029***	0.031***	0.039***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
+5	0.040***	0.033***	0.032***	0.038***	0.047***
	(0.006)	(0.006)	(0.008)	(0.007)	(0.006)
	(1)	(2)	(3)	(4)	(5)
CAPM-adj	SALE	EMP	EBIT	EBITDA	AT
+1	0.012***	0.010***	0.010***	0.012***	0.013***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
+2	0.023***	0.019***	0.014***	0.019***	0.026***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
+3	0.032***	0.027***	0.021***	0.023***	0.038***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
+4	0.041***	0.033***	0.028***	0.033***	0.046***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
+5	0.048***	0.038***	0.032***	0.042***	0.055***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)

Table A.10: Decomposition

This table reports decomposition results for our main tests for idiosyncratic volatility and firm growth. Panel A reports results for idiosyncratic volatility and Panel B reports results for firm growth. Test of extensive margin compares companies with mobile app releases v.s. companies without mobile app releases, and Test of intensive margin compares companies within the sample of mobile app releases. $1_{\{Has\}}$is an indicator variable that equals one if the firm-year observation has mobile app value greater than zero and zero otherwise. The specifications are the same as in the baseline analyses. Controls include lagged logged size, lagged volatility, and time & industry fixed effects. Standard errors are clustered by firm and reported in parentheses. Dependent variables in Panel A are multiplied by 100. Each entry represents a separate regression. Firm mobile app-value measures are normalized to have mean zero and standard deviation of one. All variables are winsorized at the 1% level using annual breakpoints. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Idiosyncratic Volatility					
		(1)	(2)	(3)	(4)
Extensive Margin		FF3	FF3 + Mom	FF5	FF5 + Mom
+1	$1_{\{Has\}}$	-0.947*	-0.976**	-1.033**	-1.046**
		(0.499)	(0.497)	(0.502)	(0.500)
+2	$1_{\{Has\}}$	-2.150***	-2.228***	-2.330***	-2.377***
		(0.645)	(0.644)	(0.644)	(0.644)
+3	$1_{\{Has\}}$	-3.186***	-3.268***	-3.390***	-3.451***
		(0.784)	(0.779)	(0.783)	(0.780)
+4	$1_{\{Has\}}$	-2.991***	-3.040***	-3.205***	-3.257***
		(0.932)	(0.929)	(0.934)	(0.933)
+5	$1_{\{Has\}}$	-3.526***	-3.659***	-3.613***	-3.762***
		(1.102)	(1.102)	(1.104)	(1.103)
		(1)	(2)	(3)	(4)
Intensive Margin		FF3	FF3 + Mom	FF5	FF5 + Mom
+1	v^{SM}	-0.624***	-0.604***	-0.613***	-0.596***
		(0.199)	(0.199)	(0.199)	(0.199)
+2	v^{SM}	-1.012***	-1.008***	-0.990***	-0.987***
		(0.257)	(0.256)	(0.256)	(0.256)
+3	v^{SM}	-1.335***	-1.328***	-1.288***	-1.284***
		(0.294)	(0.294)	(0.293)	(0.293)
+4	v^{SM}	-1.493***	-1.472***	-1.429***	-1.411***
		(0.318)	(0.318)	(0.320)	(0.320)
+5	v^{SM}	-1.833***	-1.827***	-1.796***	-1.792***
		(0.368)	(0.369)	(0.371)	(0.372)

Panel B. Firm Growth						
		(1)	(2)	(3)	(4)	(5)
Extensive Margin		SALE	EMP	EBIT	EBITDA	AT
+1	$1_{\{Has\}}$	0.006	0.003	0.026***	0.024***	0.012**
		(0.006)	(0.005)	(0.010)	(0.008)	(0.006)
+2	$1_{\{Has\}}$	0.014	0.015	0.050***	0.046***	0.032***
		(0.011)	(0.010)	(0.015)	(0.013)	(0.010)
+3	$1_{\{Has\}}$	0.017	0.025*	0.056***	0.040**	0.050***
		(0.015)	(0.014)	(0.018)	(0.017)	(0.015)
+4	$1_{\{Has\}}$	0.033*	0.035*	0.086***	0.066***	0.072***
		(0.019)	(0.018)	(0.023)	(0.021)	(0.019)
+5	$1_{\{Has\}}$	0.042*	0.045**	0.093***	0.080***	0.085***
		(0.023)	(0.023)	(0.027)	(0.025)	(0.023)
		(1)	(2)	(3)	(4)	(5)
Intensive Margin		Sale	EMP	EBIT	EBITDA	AT
+1	v^{SM}	0.018***	0.014***	0.015***	0.020***	0.019***
		(0.002)	(0.002)	(0.004)	(0.004)	(0.002)
+2	v^{SM}	0.033***	0.025***	0.017***	0.029***	0.033***
		(0.004)	(0.004)	(0.006)	(0.005)	(0.004)
+3	v^{SM}	0.047***	0.036***	0.032***	0.044***	0.048***
		(0.006)	(0.006)	(0.008)	(0.008)	(0.006)
+4	v^{SM}	0.058***	0.044***	0.040***	0.052***	0.058***
		(0.008)	(0.008)	(0.009)	(0.009)	(0.007)
+5	v^{SM}	0.068***	0.051***	0.043***	0.061***	0.069***
		(0.010)	(0.009)	(0.011)	(0.011)	(0.009)

B. Details in Estimating Mobile App Value

To estimate the market value of each mobile app, we closely follow the method of Kogan et al. (2017) and apply it to our specific mobile app context. We outline the estimation procedure in detail here and use the same notion as in Kogan et al. (2017) whenever possible to facilitate comparison.

To remove aggregate market news, we use the firm's idiosyncratic return, calculated as the firm's return minus the return on the market portfolio. This definition of idiosyncratic return assumes that firms have a constant beta loading of one with the market, and the benefit of this definition is in its simplicity which avoids estimating factor loadings. Around the event of the mobile app release, the idiosyncratic stock return contains two components—a component related to the mobile app release and a component unrelated. Therefore, the idiosyncratic stock return R for a given firm around the time that its mobile app j is released can be written and decomposed as:

$$R_j = \upsilon_j + \epsilon_j \tag{10}$$

where υ_j denotes the value of app j as a fraction of the firm's market capitalization and ϵ_j denotes the components of the firm's stock return unrelated to the mobile app.

We construct the estimate ξ of the economic value of mobile app j as the product of the estimate of the stock return due to the value of the app times the market capitalization M of the firm that is releasing the mobile app j on the day prior to the announcement of the mobile app release:

$$\xi_j = (1 - \bar{\pi})^{-1} \frac{1}{N_j} E\left[\upsilon_j | R_j\right] M_j. \tag{11}$$

If multiple mobile apps N_j are released by the same firm on the same day, we assign each mobile app a fraction $\frac{1}{N_j}$ of the total value. In our specification, we further assume that $\bar{\pi} = 0$, where $\bar{\pi}$ is the ex ante probability of the market fully expected the successful release of an app before the actually release date. This assumption, that the release is fully unexpected, likely underestimates the value of mobile apps as the releases of some mobile apps may be anticipated.

To empirically estimate ξ, one need to make assumptions about the distribution of υ and ϵ, both of which are allowed to vary across firms f and across time t. Following Kogan et al. (2017), we assume a normal distribution truncated at 0 for υ_j, $\upsilon_j \sim N^+\left(0, \sigma^2_{\upsilon ft}\right)$, and a normal distribution for the noise term, $\epsilon_j \sim N\left(0, \sigma^2_{\epsilon ft}\right)$. Therefore, the filtered value of υ_j as a function of the idiosyncratic stock return R is equal to

$$E\left[\upsilon_j|R_j\right] = \delta_{ft}R_j + \sqrt{\delta_{ft}}\sigma_{\epsilon ft}\frac{\phi\left(-\sqrt{\delta_{ft}}\frac{R_j}{\sigma_{\epsilon ft}}\right)}{1-\Phi\left(-\sqrt{\delta_{ft}}\frac{R_j}{\sigma_{\epsilon ft}}\right)} \tag{12}$$

where ϕ and Φ are the standard normal pdf and cdf, respectively, and δ is the signal-to-noise ratio,

$$\delta_{ft} = \frac{\sigma^2_{\upsilon ft}}{\sigma^2_{\upsilon ft} + \sigma^2_{\epsilon ft}}. \tag{13}$$

The conditional expectation is an increasing and convex function of the idiosyncratic firm return R. The exact shape of this function depends on the distributional assumption for υ and ϵ.

To proceed further, we need to estimate the parameters $\sigma_{\epsilon ft}$ and $\sigma_{\upsilon ft}$. If we allow both variances to arbitrarily vary across firms and across time, the number of parameters becomes quite large and thus infeasible to estimate. We therefore specify that the signal-to-noise ratio is constant across firms and time, $\delta_{ft} = \delta$. This assumption implies that $\sigma^2_{\epsilon ft}$ and $\sigma^2_{\upsilon ft}$ are allowed to vary across firms and time but in constant proportions to each other. Following Kogan et al. (2017), we set $\hat{\delta} = 0.0145$. We estimate $\sigma^2_{\epsilon ft}$ non-parametrically using the estimated realized mean idiosyncratic squared returns σ^2_{ft} and the fraction of trading days that are announcement days d_{ft} in our sample, together with the estimated $\hat{\gamma} = 0.0146$ from Kogan et al. (2017).[27]

[27] The equation is $\sigma^2_{\epsilon ft} = 3\sigma^2_{ft}(1 + 3d_{ft}(e^{\hat{\gamma}} - 1))^{-1}$. We also allow the estimate to vary at an annual frequency.