Mobile Apps, Firm Risk, and Growth

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Abstract

This paper studies the economic importance of mobile applications (apps) for firms. Using novel data, we construct a market-based app-value measure and show that it corresponds positively with the apps' utility value, measured by future downloads. Firms' app values are associated with a significant reduction in firm-specific risk, especially when the apps collect user data. Following the California Consumer Privacy Act—a plausibly exogenous shock to data-collecting ability—the relationship between app value and firm risk diminishes, and more for firms with high ex-ante California exposure. Moreover, firms' app values, particularly for data-collecting ones, predict substantial future growth.

Keywords: Mobile Application, Valuation, Data, Firm Risk, Growth

JEL-Classification: G14, L1, O3

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1 Introduction

Mobile applications (apps), from TikTok and Facebook to Google Maps, have seamlessly integrated into our daily routines. Since its inception more than a decade ago, the mobile app market has grown immensely in size and popularity. An industry report by the Global System for Mobile Communications finds that mobile technologies and services generated 5% of the global gross domestic product (GDP) in 2022 (GSMA (2023)). As of 2023, over five billion people worldwide use mobile apps for various purposes, and 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 which have released their own apps over the past decade. These digital platforms allow companies to reach customers directly, facilitating data collection that supports informed decision-making and is becoming a vital part of their operations.

For example, Starbucks's introduction of its mobile app significantly increased its data collection, enhancing the company's understanding of customers and providing invaluable insights into trends and preferences within its customer base.[2] Starbucks is just one among many; in our sample, over 690 U.S. public firms spanning most industry sectors have released more than 9,600 apps since 2008.[3] For some firms, apps as standalone assets are a significant part of their revenue sources. Despite the growing importance of the mobile app economy, our understanding of apps' economic value and their impact on firms remains limited. Leveraging a novel dataset that includes a comprehensive set of iOS apps released by U.S. publicly listed firms and building on recent theories about data and firms, our study is the first to examine the economic importance of mobile apps for firm risk, growth, and market power.

Apps could be very different and serve various purposes for firms, such as engaging

[1] See https://www.businessofapps.com/data/app-demographics/ and https://www.bbc.com/news/technology-59952557, respectively.

[2] As of 2022, Starbucks's 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, such as determining new store locations, product expansion, and menu updates. Notably, Starbucks uses the app data to personalize the customer experience, which they attribute as the largest driver of increased customer spending (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 spending, improved customer retention, and marketing efficiency (Starbucks' Q3 2019 conference call).

[3] Out of 71 two-digit SIC code sectors, 55 have public firms that have released apps.

with customers through app functionalities and generating new revenue streams through in-app purchases. To analyze the role of apps for firms, we first need a measure that can reflect the differences in their economic importance and be comparable across industries and over time. The empirical challenge is that such a measure is not directly observable. 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 by publicly listed companies. The advantage of this approach is that because stock prices are forward-looking, this measure estimates the private value to the app owners based on ex-ante information and their expectations of the app's economic importance to the firm, such as gaining access to customer data or generating additional revenue. This measure can also be useful in studying the returns on a firm's internally developed intangible assets and subsequent firm outcomes. Moreover, this market-based measure can be represented in dollar amounts and is thus comparable across different industries and over time.

The market-based measure of app value relies on the assumption that there is new information about apps at the time of app release, and investors incorporate the information in stock prices. 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 and investors react to it. Around the app release day, in addition to app-related news, stock prices may also move for other reasons unrelated to the app, even within a narrow window. To isolate the stock price movement related to the news of mobile app releases from unrelated information, we apply similar distributional assumptions as in Kogan et al. (2017) to filter the component of stock returns.[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]

[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 of the return components are used for a sample of patents, and patents can be distinct from mobile apps, the method is general and can be applied to various informational events. In robustness analyses, we also estimate key parameters for the return components using app-specific information and reach similar results.

[5]The detailed discussion is included in Section 2.3. In Appendix A.1, we also show summary statistics of the estimated app value by app categories. The top five categories with the highest average estimated app

To evaluate the usefulness of our app-value measure and whether it captures app value per se, we examine its correlation with an app's future user adoption, as indicated 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.com, a mobile app development platform, the number of an app's downloads is the primary metric most universally used for evaluating the value of an app. We find that our app-value measure is strongly and positively associated with the app's average forward weekly downloads. This relationship cannot be explained by various 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.

In the second part of the paper, we then use our app-value measures to examine the economic importance of mobile apps for firms. The value of apps may come from many components, including the revenue streams through in-app purchases and advertisements, the improvement in brand name recognition, and more. In this paper, we focus on a key component of the app value that may come from the data it collects, which is motivated by academic and policy discussions as well as by testable predictions derived from related theories (e.g., Scott Morton et al. (2019); Veldkamp (2023)). Data have been shown to play a critical role in facilitating economic decision-making (e.g., Zhu (2019); Farboodi et al. (2022a); Chemmanur et al. (2023)). Many mobile apps aggressively collect all aspects of customer information for business operations, and firms directly attribute such collected data to important business decision-making.[6] The data collection by apps also heightens debate over data protection and privacy concerns among policymakers and practitioners.[7] Importantly, there is a growing theoretical literature that studies the role of data for firms and generates predictions about how data can reduce firm uncertainty and risk (e.g., Farboodi and Veld-

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.

[6]For example, in the 2022 annual reports filed with the Securities and Exchange Commission (SEC), both Meta and AppLiov discuss the importance of data from apps in driving business strategies.

[7]For example, the U.S. Federal Trade Commission (FTC) recently indicated its intention to increase data privacy enforcement efforts against mobile apps in the case of GoodRx Holdings (FTC File No. 2023090).

kamp (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 uncertainty in making forecasts, such as those for customer demand and investment returns, thereby reducing firm-specific or systematic risks. Furthermore, the type of risk alleviated by data can lead to divergent outcomes regarding firm growth and market power. 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 how apps, by giving access to user data, enhance firm-specific information environment and affect subsequent risk and growth.[8]

Consistent with the prediction that data can reduce firm-specific risks, we find that firms' app-value measures are negatively and significantly associated with their subsequent changes in firm-specific risk, measured by idiosyncratic volatility. 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 five years. These 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 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 permanent, exhibiting a trend of increasing risk reduction over an extended period. One concern about the research design is that both the app-value measure and the firm risk measure contain return volatility. Although we find that the results are robust to controlling for return volatility and changes of volatility, one may still worry that auto-correlations of idiosyncratic volatility drive the results. To further address the concern, we use cash flow volatility as a non-return-based alternative measure of firm risk and reach similar conclusions.

[8]It is important to note that apps can have various functionalities and benefits for firms that are not mutually exclusive. However, in light of the academic and policy discussions, as well as the testable predictions regarding data and firm risk, in this paper, we focus on the data-access aspect of apps on firm risk and growth. As robustness checks, we obtain similar results when removing apps with in-app purchases and paid apps, a potentially important benefit of apps that may contribute to risk reduction and growth of firms. We return to this point in Section 6.4.

If data collection by apps is important in driving the relationship between app value and reduced firm idiosyncratic volatility, we should expect to find 1) a positive relationship between app value and data collection; and 2) firms with apps collecting data experiencing a larger decline in idiosyncratic volatility than firms with apps that don't. We manually gather information on each mobile app's data collection policy from the iOS App Store and find that, on average, apps that collect user-linked data have a higher estimated economic value compared to other apps. At the firm-year level, firms releasing data-collecting apps experience a substantial decrease in idiosyncratic volatility, approximately 6.7% over five years, compared to a reduction of about 2.4% for firms releasing apps without data collection. In addition, the disparity in risk reduction between these two groups of firms grows over time, in line with the increasing returns to data as firms accumulate and use more data (Veldkamp (2023)). Moreover, examining specific types of data collected, we repeatedly find a significant relationship between data collection and the reduction of firm risk. 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.

The previous findings are still subject to endogeneity concerns that unobserved factors may drive the results. To further address the concern, we use the California Consumer Privacy Act (CCPA) enacted in 2020 as a setting, which plausibly exogenously affected the data-collecting ability of apps. The CCPA went into effect on January 1st, 2020, and was the first comprehensive and stringent consumer privacy law passed in the United States. We focus on the CCPA because we study the mobile apps released by the U.S. publicly listed companies, and the CCPA is considered the primary and strongest[9] U.S. regulation covering app data collection. This regulation establishes a range of consumer privacy rights and business obligations related to collecting and selling personal information, which significantly curb the collection and use of user data by apps. Essentially, all firms in our sample need to comply with the regulation. We find that apps released post-2020 experience a diminished effect in mitigating their firms' risk. One concern with this test is that the results may be driven by confounding events around 2020. To address this concern, we further measure firms' exposure to CCPA using firms' average discussion about California in their major regulatory filings (Garcia and Norli (2012)). Consistent with the idea that CCPA drives the

[9] For reference, see https://www.nytimes.com/wirecutter/blog/state-of-privacy-laws-in-us/.

effect, we find the results more pronounced for companies with a high ex-ante California exposure.

We also examine the systematic risks of firms and do not find a statistically significant association with firms' app-value measures. Together with our previous results, they suggest that while mobile apps can reduce firm-specific risks, they do not significantly affect firms' systematic risks. According to 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. Charoenwong et al. (Forthcoming) also posit that a reduction in uncertainty can lead to higher firm productivity. Our analyses provide evidence supporting this line of predictions. First, we find a positive and significant association between firms' app-value measures and 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. Importantly, the effects are more pronounced when apps collect user-linked data. Next, 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 five years. Together, the findings reveal a strong relationship 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 our analyses on both 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 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. This suggests that the market-based app-value measure contains more information than the download-based measure in predicting firm risk and growth. 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 a larger reduction in firm risk and a 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 a larger effect on firm risk and growth than low app-value estimates. Third, we do not find strong evidence of a relationship between competitor app releases and firm growth, suggesting that a firm's app releases do not negatively affect competitors in the same industry.

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)), healthcare 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)). 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. Bian et al. (2023) discuss how Apple's requirement of iOS apps to disclose their data protection practices affects app users through downloads.[10] To the best of our knowledge, this study is the first to systematically measure the economic value of apps and examine their effects on firm 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. Several studies emphasize data as information (e.g., Begenau et al. (2018); Acemoglu et al. (2019); Bergemann and Bonatti (2019); Farboodi et al. (2022b); Eeckhout and Veldkamp (2022)). Empirical research examines the role of data in specialized markets such as media (e.g., Athey and Gans (2010);

[10]In the marketing and management literature, there are studies on mobile apps and announcement returns, such as Boyd et al. (2019) and Qin et al. (2017).

Athey and Mobius (2012)), 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. This literature has spent considerable effort in estimating the value of internally generated intangible assets, such as patents (see review by Crouzet et al. (2022)). The most notable and related work is Kogan et al. (2017) that pioneer a new method to extract the private economic value of patents from stock returns. Several papers use the estimated private economic value of patents (e.g., Kogan et al. (2020); 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 as 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. 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 discuss our data sources and use the unique app dataset to construct an empirical estimate of each mobile app's economic value, 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). In the U.S., iOS accounts for more than 60% of the mobile app market.[11]

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 app parent companies if they are listed on major stock exchanges. We download all apps with parent firms 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.[12] 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 each app's release date and primary category 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 each app's estimated weekly active users, available from August 2015 to December 2021 for a subset of the apps. An active user is defined as any phone or iPad user with at least one session during a specific period. Users who engage in more than one session during the selected period still only count as one active user. The weekly active user measure counts users with 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 various modeling techniques for data extrapolation.

[11] see https://backlinko.com/iphone-vs-android-statistics.

[12] 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.

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 to compute return volatility and market capitalization. We also require the sample of firm-year observations to have non-missing 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 by U.S. public firms.[13] Figure 1 shows the cumulative count of apps in our sample. We discuss each measure in greater detail in the corresponding analysis section.

2.2 Estimating the Economic 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 B. 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, update their information 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. This market-based measure of app value relies on the assumption that there is new information about apps at the time of app release, and investors incorporate the information in stock prices. 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.

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

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

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.[14] 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 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 (R), 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 (υ) and a component unrelated (ϵ). 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

[14]Some apps (approximately 11%) are released on the weekend. In such cases, we consider the subsequent Monday as the release day to match the 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.

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 B. In addition, the procedure requires estimating two parameters, $\sigma^2_{\upsilon ft}$ and $\sigma^2_{\epsilon ft}$, 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).[15] 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 app sample. We also allow the estimate to vary at an annual frequency.

Lastly, the economic value of a mobile app in dollars, denoted as ξ, is calculated as the product of the component related to the mobile app release ($E\left[\upsilon|R_f\right]$), the market capitalization of the firm, and the inverse of the unconditional probability that the market does not anticipate the app release. 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, which is specific to our app context and different from the estimate for patent application in Kogan et al. (2017). 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

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). The average (median) idiosyncratic firm return (R) is 0.13%

[15] In Section 6.2, we re-estimate the signal-to-noise ratio using our sample to construct the app value measure. The results remain similar.

(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%.[16] 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, Meta acquired Instagram, which is largely an app company, for approximately $1 billion in 2012, and then WhatsApp for $19 billion in 2014. 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.[17] 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.

Another comparison is based on venture capital (VC) financing for mobile app start-ups in the U.S. from the Preqin Venture Deals Database. The average (median) total funding

[16] 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 ($E\left[v|R_f\right]$). In the estimation model, R can be negative even if the app value is assumed to be non-negative because R contains both a component related to the mobile app release and an unrelated component, the latter of which can be negative.

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

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, Crunchbase.com estimates the average level of VC ownership at exit to be 50%. Assuming an average of 50% VC ownership would imply an estimated value of \$103.4 (\$14.4) million for the average (median) app firm at the exit stage, which is comparable to our estimated app values.

Additionally, our estimates could be an underestimation of the actual value of mobile apps, given 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.[18]

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. If firm i releases no apps in year t, both variables equal zero.

We present the summary statistics of firm-level measures in Table 2. The table reports the two firm-level mobile app-value measures, logged firm size (market capitalization), idiosyncratic volatility (estimated $\sigma_{\epsilon ft}$), as well as the logged growth rates of idiosyncratic volatility, sales (COMPUSTAT sale), employment (COMPUSTAT emp), EBIT (COMPUSTAT ebit), EBITDA (COMPUSTAT ebitda), and total assets (COMPUSTAT at). 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 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 assets. The distribution of the average firm-level app-value measures reveals substantial heterogeneity across industries. 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

In this section, we 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

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

to compare with. In the mobile app market, a commonly used and important metric for indicating mobile app value is the average number of weekly downloads. This metric assesses user adoption of an 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.[19] Accordingly, 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.[20] Specifically, we relate the future average number of weekly downloads $\boldsymbol{D}_j$ 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 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 a 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.

[19]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.

[20]The research design is in a similar spirit to Kogan et al. (2017) who regress patent value on future patent citations. In addition, the results are robust to using alternative download measures for each app, including the average daily downloads and total downloads. The results are also robust to regressing forward user downloads on app-value 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.[21] An alternative app-based metric for the value of mobile apps is the number of active users. 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. 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).

[21]Results are similar when only considering apps released after 2012, which is the beginning of the app download dataset. We also obtain similar results when we only measure average weekly downloads within the first few years after an app is released. Moreover, we include the forward average weekly number of version updates as an additional control and find robust effects of the weekly downloads.

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. We specifically focus on how these apps, by facilitating access to user data, affect firms. Moreover, 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 firms' usage of data in decision-making processes and propose that data, as digitized information, can reduce firm risks by reducing uncertainty around making forecasts. Importantly, they differentiate between firms' idiosyncratic risk and systematic risk, each having distinct effects on firm growth and market power. A reduction in firms' idiosyncratic risk increases 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 different firm risks. In the subsequent section, 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 $v \in \left\{v^{sm}, v^{dw}\right\}$ 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 firms.[22] We normalize firm-level mobile app values 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.

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 the 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. As a robustness check that the observed effect is not driven by firms' general investment strategies, in Table A.3 of the Internet Appendix, we show that the results are qualitatively similar after controlling for a wide range of firm investments (physical assets, R&D, SG&A), alongside the Kogan et al. (2017) patent value measure and investment opportunity (Tobin's Q).[23] In addition, we confirm that the results are robust including the lag value of the dependent variable. Furthermore, we examine the effect of app value on firm risk in each of Fama-French five industries, and find consistent results in all industry groups.

[22]Because the sample has a relatively short time period, the main model specification clusters standard errors by firm and not by time, as suggested by Petersen (2008) and Thompson (2011). Nevertheless, in untabulated robustness analyses, we cluster standard errors by both firm and year, and find that the majority of the results in the paper remain statistically significant at 5% percent level.

[23]Moreover, in untabulated results, we include an indicator variable for the year prior to app releases and find no significant coefficient estimate of the indicator, suggesting that the app-value effect on firm risk is unlikely to be anticipated.

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 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}. When both v^{sm} and v^{dw} are included in Panel B of Table 5, 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, facilitate decision-making 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 perceived by shareholders.[24]

[24] 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. In a later test in Section 4.5, we find that systematic risks do not change significantly, which is consistent with mobile apps leading to a reduction in firm-specific risks instead of an increase in price co-movement.

4.2 Cash Flow Volatility

In our main results, we use stock returns to measure firm volatility. The advantages of using return volatility are two-folds: 1) return data are available daily, enabling us to measure return volatility with relative precision; and 2) it is easy to separately examine idiosyncratic versus systematic risks with return data. However, one concern is that the construction of the app-value measure contains return volatility. Although the results are robust to controlling for return volatility and changes of volatility, one may still worry that the results are driven by auto-correlations of idiosyncratic volatility. Moreover, returns capture news not only about a company's cash flows but also about discount rates. Therefore, in this subsection, we use an alternative, non-return-based measure of firm volatility–cash flow volatility–to study the relationship between mobile app value and changes in firm volatility.

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 model 4, changing y to be 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 $\tau >= 3$.

Table 6 presents the results. 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.

4.3 Data Collection of Mobile Apps and Firm Risk

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 data it collects. In this subsection, we provide further evidence of the importance of apps' data collection in reducing 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 its homepage in the iOS App Store. The app policy specifies what data linked to users are being collected, such as location, contact, search history, and product interaction. 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. If data collection is important in driving the relationship between app value and the decrease in firms' idiosyncratic volatility, we would expect that (i) apps collecting user-linked data are valued more highly and (ii) firms with apps collecting data experience a greater reduction in idiosyncratic volatility compared to other firms.

Panel A of Table 7 reports the summary statistics of firm app-value measures with or without data collection. On average, apps that collect user-linked data have a much higher estimated economic value than other apps. In Panel B of Table 7, 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 is 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 6.7% for companies that release apps that collect user-linked data at the five-year horizon, while it only decreases by 2.4% for companies that release other apps. One interesting observation is that the coefficient estimate of β^{Other} is also statistically significant in some model specifications. Although the magnitude is much smaller than that of β^{Data}, the results suggest that apps without collecting user-linked data may still contribute to reducing firm risk, pointing to other potential beneficial features for firms. For example, firms could use the aggregate data from app usage to understand the business better.

We also examine the effect of different types of user-linked data on firm risk and report the results in Table A.5 of the Internet Appendix. There are 29 different types of user-linked data collected in total by our sample of apps. We categorize the user-linked data into six groups: personal information (e.g., name and ID), contact information (e.g., email), user phone content (e.g., photos and videos), app usage (e.g., product interaction and purchase/search/browsing history), financial information (e.g., payment and credit), and diagnostic data (e.g., crash data). We construct similar indicator variables for firm-years that collect a given type of user-linked data. Across all data types, there is a significant relationship between data collection and the reduction of firm risk over horizons of two to five years. 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).

4.4 Data Privacy Rule

To address endogeneity concerns that confounding variables may drive the relationship between app value and firm risk, we use the California Consumer Privacy Act (CCPA) enacted in 2020 as a setting, which plausibly exogenously affected the data-collecting ability of apps. The CCPA went into effect on January 1, 2020, and was the first comprehensive and stringent consumer privacy law passed in the U.S., setting significant privacy standards and obligations for businesses concerning the collection and sale of personal information. It grants California residents rights to access, delete, and control the use and disclosure of their data, including opting out of its sale. The CCPA applies to for-profit entities that collect personal information from California residents, manage the processing of that information, conduct business in California, and meet any of the following criteria: 1) have gross annual revenue of over $25 million; 2) buy, sell, or share the personal information of 100,000 or more California residents or households; or 3) derive 50% or more of their annual revenue from selling or sharing California residents' personal information.

In essence, the CCPA rule applies to any business regardless of its location and has the potential to limit data collection and usage by apps significantly. Given that the firms in our sample are publicly listed, can easily meet the first criteria, and are likely to serve California residents, they are likely subject to the CCPA provisions. Accordingly, we hypothesize that apps released by our sample firms after 2020 have a reduced impact on mitigating firm risk. In Table 8, we regress changes in firm risk on an interaction term between v^{sm} and a $\boldsymbol{Post}$ indicator, which equals one for years since 2020 and zero for previous years. We also include the interactions of $\boldsymbol{Post}$ and control variables. Due to limitations in data availability post-2020, we measure changes in firm risk over a two-year horizon. Column (1) shows that the interaction term is positive and statistically significant at the 1% level, consistent with a reduction in the effect of app value on the reduction of firm risk following the introduction of the CCPA. In Column (2), we restrict the sample to firm-years with app releases and reach similar conclusions.[25]

One concern with this test is that the post-2020 indicator may capture the effect of other confounding events, such as the EU's General Data Protection Regulation enacted in 2018, or the privacy policy changes in the iOS store in December 2020. To mitigate this concern, we examine firms' exposure to CCPA more closely, leveraging the heterogeneity in how different firms are affected by the CCPA to support the notion that the observed effects are likely driven by CCPA rather than other events. The challenge is that CCPA affects all companies that collect data from California residents, regardless of where the company is located, and data on a firm's number of Californian residents is unavailable. To this end, we gauge a firm's exposure to California regulation based on the average discussion about California in its major regulatory filings. Specifically, we measure a firm's California exposure as the average mentions of "California" over the average number of total words across their 10-K, 10-Q, and 8-K reports filed with the SEC before 2020, following the methodology of Garcia and Norli (2012). We use all major regulatory filings to more comprehensively capture firms' total exposure to California regulation. Although this measure is unlikely to capture each firm's precise exposure to the CCPA, our identification is valid as long as the measure captures the relative exposure of our sample firms to California policies in the cross-sectional.

In Columns (3) and (4) of Table 8, we construct an indicator variable $\boldsymbol{CA}$ that equals one for firms with above-median California exposure measured prior to 2020. We also include

[25] Using a one-year horizon generates similar results. We also obtain similar results if we restricted the sample to a balanced period of two years before and after 2020. In addition, we find that the effect of apps on firm risk is less pronounced for data-collecting apps after CCPA.

interactions of CA with control variables. We find that the triple interaction term $v^{sm} \times Post \times CA$ is positive and significant at the 5% level, indicating that the effect is more pronounced for companies with high ex-ante California exposure, supporting the inference that CCPA is the likely driver of the observed effects.[26]

4.5 Systematic Risk

Next, we study the relationship between the firm-level market-based app-value measure and firm systematic risk as measured by market beta based on the Fama-French 3-factor model.[27] Table A.6 in the Internet Appendix shows that changes in subsequent market beta are not statistically significantly associated with firms' app-value measures. 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.

Our findings indicate that the mobile app-value measure is significantly and negatively associated with firms' idiosyncratic volatility but is not related to their market beta, suggesting that mobile apps mainly reduces firm-specific risk rather than systematic risk. According to Eeckhout and Veldkamp (2022), this reduction in risk could lead to increased firm growth and market power, which we examine in the next 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, consequently, have more market power. Charoenwong et al. (Forthcoming) also posit that a reduction in uncertainty can lead to higher firm productivity. Building on our previous findings, in this section, we examine whether the economic value of apps is positively associated with firm growth and market

[26]Our results suggest that future research using iOS store privacy policy as a shock to privacy data collection should consider the effect of CCPA.

[27]Using alternative factor models generates similar results.

share. We use market-based and download-based app-value measures to test these theoretical predictions.

5.1 Mobile App Value and Firm Growth

We use the same regression specification as in the previous section to examine the relationship between the firms' app-value measure and 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 $v \in \left\{v^{sm}, v^{dw}\right\}$. 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 firms. We normalize firm-level mobile app values to have a mean of zero and a standard deviation of one so that the point estimates are comparable across different specifications.

Table 9 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. To address the concern that growing firms may invest more and are also more likely to develop valuable apps, in Table A.7 of the Internet Appendix, we show that the results are qualitatively similar after controlling for firm investments (physical assets, R&D, SG&A), the Kogan et al. (2017) patent value measure, and investment opportunity.

Next, we compare the market-based measure of mobile app value (v^{sm}) with the download-weighted app-value measure (v^{dw}). Panel A of Table 10 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}. The results are consistent with the common industry practice of using app adoption to infer the app's value. Panel B of Table 10 includes both measures as predictors to examine whether these two measures contain independent information regarding firms' future growth. 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. 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.

We also examine the role of data in driving the effect of app-value measures on firm growth. We conduct similar analyses as in Section 4.3. Table 11 presents the results. We find that β^{Data} is consistently larger than β^{Other} over all horizons and across different measures of firm growth. The gap between β^{Data} and β^{Other} also tends to increase over the horizons. The findings suggest that having access to user data is important in driving the effect of app value on firm growth.[28]

5.2 Mobile App Value and Market Share

Lastly, 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 12 presents the results. Panels A and B report results using firms' asset share and revenue share, respectively. When evaluated independently, both the market-based

[28] In untabulated results, we find evidence that the effects of app value on sales and total assets are reduced following CCPA.

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} (v^{dw}) corresponds to an approximate 4.0% (2.1%) increase in market share based on firms' asset share and a 3.4% (1.8%) increase based on firms' revenue share.[29] 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. For example, at the five-year horizon, 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. Our results are largely consistent with the predictions in Eeckhout and Veldkamp (2022) on the investment-data complementarity channel in increasing firms' market power.

6 Additional Results and Robustness Checks

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

6.1 Competitors' Mobile App and Firm Growth

We 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:

$$v_{I\setminus i,t} = \frac{\sum_{i' \in I\setminus i} \sum_{j \in M_{i,t}} \xi_j}{\sum_{i' \in I\setminus i} AT_{i',t-1}}, \tag{7}$$

[29] In Table A.7 of the Internet Appendix, we also 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.

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:

$$y_{i,t+\tau} - y_{i,t} = \beta \times v_{I\backslash i,t} + \gamma \times Z_{i,t} + \epsilon_{i,t+\tau}. \tag{8}$$

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.9 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 measures of firm growth, only employment growth exhibits a statistically significant and negative relationship with $v_{I\backslash i,t}$.[30]

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 app releases and firm growth. This result highlights the difference between patents and mobile apps as intangible assets. In particular, a firm's app releases do not negatively affect competitors in the same industry.

6.2 Sensitivity Tests of App Value Estimates

In our main specification, we set the signal-to-noise ratio δ to 0.0145 and calculate idiosyncratic returns as the difference between firm returns and market returns following Kogan et al. (2017). 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 estimate the signal-to-noise ratio using our test sample and denote the ratio as $\hat{\delta}_{app} \approx 0.024$.[31] Second, we calculate the idiosyncratic return based on the CAPM model

[30]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.

[31]To estimate δ_{app}, we regress the log squared returns on an app release window indicator variable (I) for the sample of firm-years with 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

to estimate app value. Table A.10 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 variations in the signal-to-noise ratio and the calculation of idiosyncratic returns.

6.3 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.11 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. The results also suggest that the effects of app-value estimates are more general and not just driven by the assumptions in the estimation of the market-based measure. 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.

6.4 Additional Discussion

In this paper, we focus on the data-access aspect of apps in driving changes in firm risk and growth. Our focus on this app aspect is motivated by academic discussions and anecdotal evidence from firm discussions in financial statements and conference calls. Moreover, our results are consistent with theoretically motivated predictions on the value of apps through data access. It is important to note that apps can have various functionalities and benefits for firms that are not mutually exclusive. Although it is not clear conceptually how the other channels may affect firm risk, as robustness checks, we examine an important benefit

variance of the measurement error based on $\hat{\delta}_{app}$.

of apps for firms–generating revenue streams through in-app purchases or paid apps. In Table A.12 of the Internet Appendix, we rerun our baseline analyses after excluding apps with in-app purchases and paid apps. We continue to find similar results as our main findings. Nevertheless, we acknowledge that it is not possible for us to fully investigate all app functionalities, and we leave these features to future research.

7 Conclusion

In this paper, we examine the economic importance of mobile apps for firms. We do so by developing a novel measure to quantify the economic value of mobile apps using a unique dataset. Our measure, based on stock returns following the method of Kogan et al. (2017), 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 app-value measures and firms' risk, growth, and market power. Motivated by both academic and policy discussions as well as related theoretical predictions (e.g., Scott Morton et al. (2019); Veldkamp (2023)), we focus on how these apps, by giving access to customer data, potentially reduce the uncertainty of business decisions, affecting subsequent firm risk and 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, using the California Consumer Privacy Act enacted in 2020 as a setting, which plausibly exogenously affected the data-collecting ability of apps, we find that apps released following the Act have a reduced impact on mitigating firms' risk, especially for firms with high ex-ante California exposure. Consistent with the predictions in Eeckhout and Veldkamp (2022) on the investment-data complementarity channel, we find that firms' mobile app value is positively and significantly associated with substantial firm growth and increases in market power. The findings highlight mobile apps as important intangible assets in shaping firm risk and growth and have policy implications for the role of apps' data collection in firm outcomes.

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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}), the logged growth rate in firm idiosyncratic volatility ($\Delta idiovol_{ff5}$ calculated based on Fama-French 5-factor models), and changes in firm sales, employment, EBIT, EBITDA, and total asset. 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: Mobile App Value and Cash-Flow Volatility

This table reports regression estimates of model 4 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)

Table 7: Data Collection and Idiosyncratic Volatility

This table reports results related to app data collection and firm idiosyncratic volatility. Panel 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 ($1_{\{Data\}}$ and $1_{\{Other\}}$). 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 pair of entries 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})	4.43	2.65	1.79***
Std. Dev (v^{sm})	0.14	0.08	

Panel B		(1)	(2)	(3)	(4)
		FF3	FF3 + Mom	FF5	FF5 + Mom
+1	β^{Data}	-1.404	-1.473*	-1.457*	-1.491*
		(0.886)	(0.886)	(0.883)	(0.884)
	β^{Other}	-0.809	-0.822	-0.917	-0.920
		(0.588)	(0.586)	(0.592)	(0.591)
+2	β^{Data}	-3.691***	-3.834***	-3.800***	-3.900***
		(1.083)	(1.080)	(1.083)	(1.080)
	β^{Other}	-1.682**	-1.745**	-1.897***	-1.930***
		(0.734)	(0.730)	(0.731)	(0.730)
+3	β^{Data}	-5.066***	-5.122***	-5.248***	-5.286***
		(1.364)	(1.358)	(1.364)	(1.356)
	β^{Other}	-2.513***	-2.607***	-2.724***	-2.797***
		(0.896)	(0.890)	(0.895)	(0.891)
+4	β^{Data}	-6.836***	-6.917***	-6.995***	-7.084***
		(1.575)	(1.573)	(1.582)	(1.579)
	β^{Other}	-1.580	-1.620	-1.815*	-1.856*
		(1.024)	(1.020)	(1.025)	(1.023)
+5	β^{Data}	-6.507***	-6.645***	-6.727***	-6.820***
		(1.837)	(1.832)	(1.838)	(1.831)
	β^{Other}	-2.384**	-2.525**	-2.438**	-2.604**
		(1.196)	(1.198)	(1.194)	(1.196)

Table 8: Data Privacy Rule and Idiosyncratic Volatility

This table reports results related to app value and firm idiosyncratic volatility around the California Consumer Privacy Act (CCPA) enacted in 2020. In Columns (1), we interact v^{sm} with $Post$, which equals one for the year 2020 and after, and zero otherwise. In Column (2), we restrict the sample to firm-years with app releases. In Columns (3) and (4), we further interact with an indicator variable CA that equals one if the company has above-sample-median California exposure measured before 2020. The California exposure measure is the average number of the phrase "California" over the average number of words across firms' 10-Ks, 10-Qs, and 8-Ks, the top three regulatory filings, in the five years before 2020. Firm-level idiosyncratic volatility is calculated based on the Fama-French 3-factor model over a two-year horizon. Controls include v^{sm}, lagged logged size, lagged volatility, time & industry fixed effects, and the interactions between the characteristics and $Post$. For Columns (3) and (4), interactions between the characteristics and CA and the interaction between $Post$ and CA are also included. Standard errors are clustered by firm and year, and reported in parentheses. 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)
	Full Sample	App Sample	Full Sample	App Sample
$v^{sm} \times Post$	1.464***	1.634***	-0.538	-0.229
	(0.334)	(0.335)	(0.657)	(0.705)
$v^{sm} \times Post \times CA$			1.714**	1.964**
			(0.591)	(0.698)
Interaction Terms	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Observations	40,528	2,289	32,181	1,996
R^2	0.346	0.365	0.375	0.394

Table 9: 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 the logged change in firm sales, employment, EBIT, EBITDA, or asset, 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 10: 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 the logged change in firm sales, employment, EBIT, EBITDA, or asset, 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 11: Data Collection and Firm Growth

This table reports results related to app data collection and firm growth. We regresses changes in future firm growth on indicator variables for mobile apps that collect data and for other mobile apps, respectively ($1_{\{Data\}}$ and $1_{\{Other\}}$). Firm growth is measured by one of firm sales, employment, EBIT, EBITDA, and asset. 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. Each pair of entries 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)	(5)
		SALE	EMP	EBIT	EBITDA	AT
+1	β^{Data}	0.017	0.012	0.054***	0.036**	0.021**
		(0.010)	(0.010)	(0.017)	(0.015)	(0.010)
	β^{Other}	0.002	0.000	0.018*	0.022**	0.010*
		(0.006)	(0.005)	(0.011)	(0.009)	(0.006)
+2	β^{Data}	0.038**	0.038**	0.091***	0.082***	0.075***
		(0.018)	(0.018)	(0.025)	(0.022)	(0.019)
	β^{Other}	0.005	0.008	0.037**	0.034**	0.016
		(0.011)	(0.010)	(0.016)	(0.013)	(0.010)
+3	β^{Data}	0.061**	0.060**	0.133***	0.092***	0.096***
		(0.027)	(0.028)	(0.031)	(0.032)	(0.027)
	β^{Other}	0.003	0.014	0.030	0.023	0.035**
		(0.015)	(0.014)	(0.019)	(0.017)	(0.014)
+4	β^{Data}	0.070**	0.072*	0.187***	0.121***	0.123***
		(0.035)	(0.037)	(0.037)	(0.037)	(0.034)
	β^{Other}	0.021	0.023	0.053**	0.050**	0.054***
		(0.019)	(0.018)	(0.024)	(0.021)	(0.019)
+5	β^{Data}	0.081*	0.089*	0.173***	0.119***	0.157***
		(0.043)	(0.048)	(0.045)	(0.045)	(0.044)
	β^{Other}	0.030	0.032	0.068**	0.070***	0.061***
		(0.022)	(0.021)	(0.029)	(0.026)	(0.023)

Table 12: 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)

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.

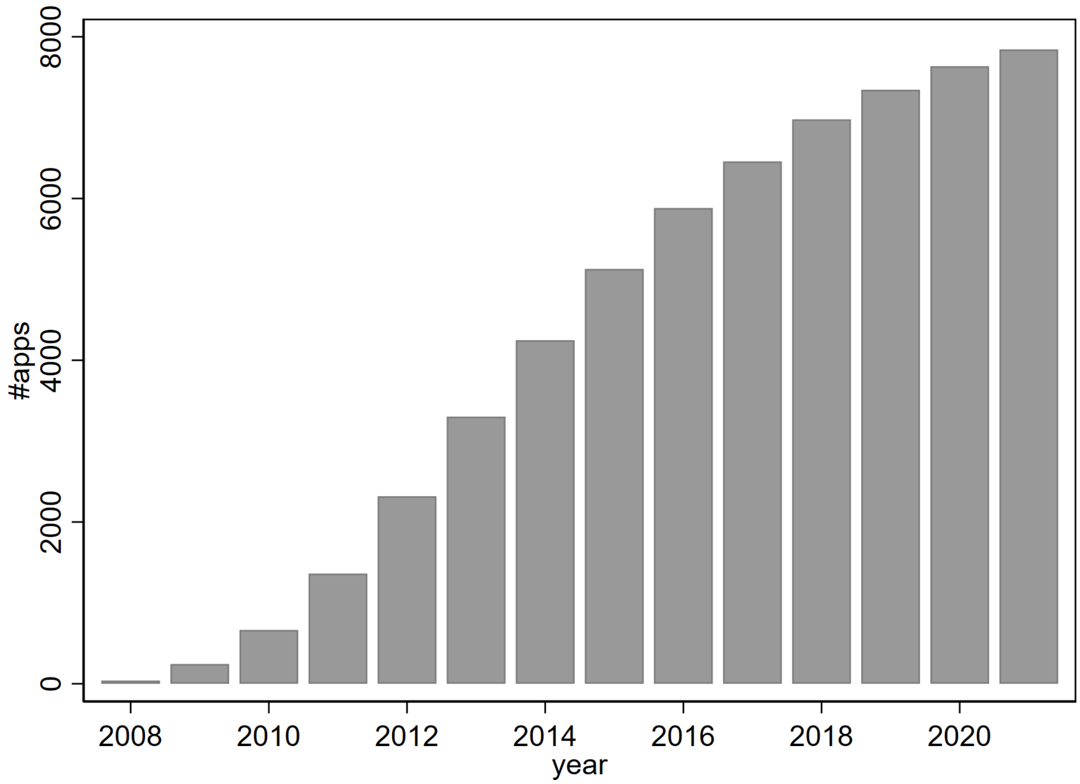
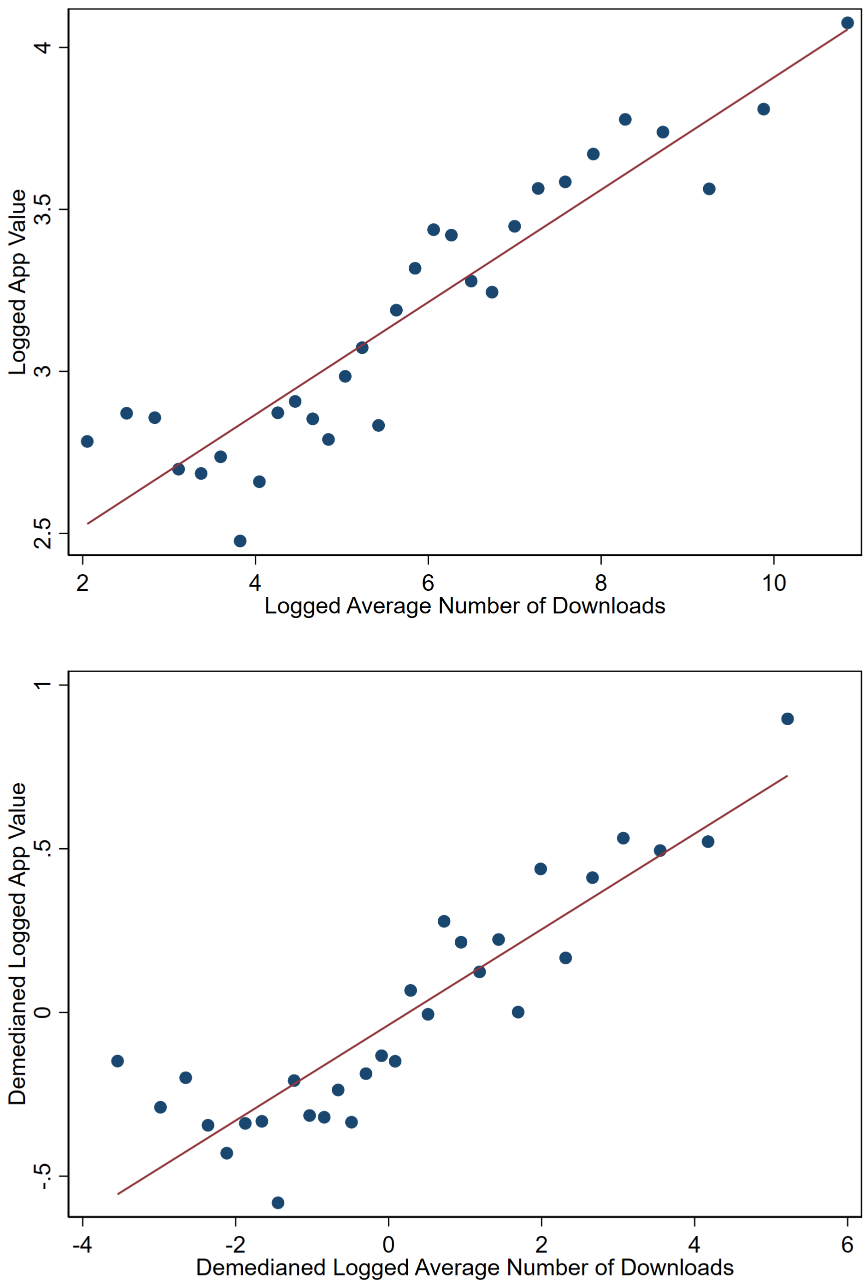


Figure 2: Relation between Mobile App Value and Future Average Download

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.



Internet Appendix

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 with 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)
$\log\left(A_j\right)$	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 (COMPUSTAT capx), R&D rate (COMPUSTAT xrd), SG&A rate (COMPUSTAT xsga), Tobin's Q (total of market capitalization and COMPUSTAT dlc and dltt, scaled by total assets), 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: Type of Data Collected and Idiosyncratic Volatility

This table reports results related to app data collection and firm idiosyncratic volatility. We regresses changes in firm idiosyncratic volatility on indicator variables for mobile apps that collect user-linked data of the type indicated by the column name, and for other mobile apps, respectively ($1_{\{DataType\}}$ and $1_{\{Other\}}$). The panel presents results for horizons of one to five years. Firm-level idiosyncratic volatility is calculated based on the Fama-French 3-factor model. 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 pair of entries 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)	(5)	(6)
		Personal Info	Contact Info	User Content	App Usage	Financial Info	Diagnostic
+1	β^{Data}	-1.587*	-1.122	-1.901	-1.282	-1.766	-1.157
		(0.922)	(1.001)	(1.193)	(0.987)	(1.890)	(1.135)
	β^{Other}	-0.813	-0.780	-0.797	-0.787	-0.753	-0.763
		(0.589)	(0.587)	(0.589)	(0.590)	(0.588)	(0.591)
+2	β^{Data}	-3.629***	-3.832***	-4.588***	-3.253***	-3.095*	-3.337**
		(1.164)	(1.196)	(1.432)	(1.230)	(1.880)	(1.399)
	β^{Other}	-1.660**	-1.643**	-1.630**	-1.612**	-1.496**	-1.561**
		(0.734)	(0.732)	(0.732)	(0.734)	(0.729)	(0.733)
+3	β^{Data}	-5.424***	-5.264***	-5.823***	-5.385***	-4.895**	-7.529***
		(1.441)	(1.495)	(1.777)	(1.585)	(2.195)	(1.848)
	β^{Other}	-2.509***	-2.457***	-2.420***	-2.465***	-2.261**	-2.448***
		(0.896)	(0.895)	(0.894)	(0.895)	(0.894)	(0.893)
+4	β^{Data}	-6.863***	-7.265***	-8.962***	-7.373***	-6.322***	-9.727***
		(1.654)	(1.646)	(2.024)	(1.743)	(2.265)	(1.915)
	β^{Other}	-1.544	-1.511	-1.495	-1.523	-1.220	-1.478
		(1.023)	(1.021)	(1.021)	(1.022)	(1.014)	(1.018)
+5	β^{Data}	-6.788***	-6.788***	-7.465***	-7.812***	-4.998*	-9.701***
		(1.913)	(1.913)	(2.405)	(2.055)	(2.788)	(2.446)
	β^{Other}	-2.368**	-2.340**	-2.256*	-2.371**	-2.018*	-2.303*
		(1.194)	(1.188)	(1.190)	(1.190)	(1.177)	(1.186)

Table A.6: 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^{Market}		
(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.7: 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 the logged change in firm sales, employment, EBIT, EBITDA, or asset, 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 (COMPUSTAT capx), R&D rate (COMPUSTAT xrd), SG&A rate (COMPUSTAT xsga), Tobin's Q (total of market capitalization and COMPUSTAT dlc and dltt, scaled by total assets), 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.8: 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 (COMPUSTAT capx), R&D rate (COMPUSTAT xrd), SG&A rate (COMPUSTAT xsga), Tobin's Q (total of market capitalization and COMPUSTAT dlc and dltt, scaled by total assets), 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.9: Competitor Mobile App Value and Firm Growth

This table reports regression estimates of model 8 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 the logged change in firm sales, employment, EBIT, EBITDA, or asset, and competitors' app value is measured as in equation 7 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.10: 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)
δ = 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.11: 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)

Table A.12: Mobile App Value and Idiosyncratic Volatility – Alternative Channel

This table reports regression outputs for firm-specific idiosyncratic volatility using the sample that removes mobile apps with in-app purchases and paid apps. 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. 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	-0.645***	-0.632***	-0.654***	-0.644***
	(0.125)	(0.125)	(0.126)	(0.125)
+2	-1.065***	-1.080***	-1.075***	-1.090***
	(0.144)	(0.142)	(0.144)	(0.143)
+3	-1.609***	-1.609***	-1.600***	-1.606***
	(0.178)	(0.178)	(0.180)	(0.179)
+4	-1.744***	-1.730***	-1.736***	-1.734***
	(0.201)	(0.201)	(0.204)	(0.205)
+5	-2.005***	-2.015***	-1.991***	-2.013***
	(0.233)	(0.234)	(0.236)	(0.237)

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:

$$R_j = \upsilon_j + \epsilon_j \tag{9}$$

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:

$$\xi_j = (1 - \bar{\pi})^{-1} \frac{1}{N_j} E\left[\upsilon_j | R_j\right] M_j. \tag{10}$$

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

$$E\left[\upsilon_j | R_j\right] = \delta_{ft} R_j + \sqrt{\delta_{ft}} \sigma_{\epsilon ft} \frac{\phi\left(-\sqrt{\delta_{ft}} \frac{R_j}{\sigma_{\epsilon ft}}\right)}{1 - \Phi\left(-\sqrt{\delta_{ft}} \frac{R_j}{\sigma_{\epsilon ft}}\right)} \tag{11}$$

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

$$\delta_{ft} = \frac{\sigma^2_{\upsilon ft}}{\sigma^2_{\upsilon ft} + \sigma^2_{\epsilon ft}}. \tag{12}$$

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).[32]

[32]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.