Acquisition of Customer Information and Corporate Decision Making

ABSTRACT

This study examines whether and under what conditions customer data collected through mobile apps—primarily for marketing purposes—aids investing and production decisions. After firms release a mobile app, (i) the accuracy of management earnings and revenue guidance increases; and (ii) firms exhibit less underinvestment in capital assets and less overinvestment in inventory, particularly when they have effective internal information systems and the mobile app collects customers' location and financial information. These findings are consistent with the notion that information obtained through mobile apps leads to improved forecasts of customer demand and thus more efficient investing and production decisions. We also find that privacy regulations intended to protect customers restrict firms' ability to access these efficiency gains.

I. INTRODUCTION

Firms invest heavily in the acquisition of customer data because it enables them to target potential customers more effectively, tailor their offerings to individuals, and improve customer satisfaction and retention (Hagel and Rayport 1997). Although firms collect this data primarily for use in marketing and managing customer relationships, it may also have value in other important business decisions. We examine whether and under what conditions technologies that allow firms to collect customer information for marketing purposes also facilitate investing and production decisions. Further, we investigate whether privacy regulations intended to protect customers restrict firms' ability to access these efficiency gains.

To examine these questions, we focus on a technological solution that allows firms to systematically collect customer information: mobile apps. Mobile apps are an increasingly important channel by which firms interact with and learn about their customers. Customers spent over 110 billion hours on mobile shopping apps in 2022, browsing new products, making and tracking purchases, and communicating with service agents (Sydow 2023). Revenue generated through mobile apps reached $3.6 trillion worldwide in 2022, nearly three times the revenue generated just five years earlier (Curry 2024). With customers increasingly using mobile shopping

apps, firms have access to greater amounts of customer data that can provide timely and valuable insights that would be difficult to collect and analyze outside of these apps. Although customer data is available from other sources, mobile shopping apps allow for real-time data collection in greater detail and wider scope, including for example the collection of GPS location and data acquired from third-party data providers linked through device identifiers.

Prior research shows that mobile apps allow firms to improve their marketing programs (e.g., Peng, Chen, and Wen 2014; Kim and Yu 2016). Data collected through mobile apps may also be useful in investing and production decisions, to the extent it allows for not only increased sales through enhanced marketing efforts but also improved forecasting of future sales that supports these decisions. For example, by leveraging customer information, firms can make more efficient capital investment decisions, i.e., they will exhibit less *underinvestment* in response to uncertainty about investment returns, and can better manage inventory levels, i.e., they will carry less excess inventory as a buffer against unanticipated demand.

Consistent with our hypotheses, we document improvements in capital investment and inventory efficiency following the release of a mobile app. Additional analyses reveal that these improvements (i) increase in the quality and quantity of customer data collected, particularly customers' location and financial information, (ii) appear quickly for inventory but only after two years for capital investment, (iii) are concentrated in firms with effective internal information systems, suggesting the value of customer data collected through mobile apps depends on adequate technological infrastructure, and (iv) are concentrated in situations where information is critical, such as when product market competition is high or during industry downturns.

Next, we investigate three customer privacy initiatives that reduced firms' ability to collect and use customer information. Studying these initiatives can inform regulators about possible

unintended consequences of their actions, and has the added benefit of addressing endogeneity concerns in our primary tests. Firms choose to release apps, so firms that release apps may differ along observable and unobservable dimensions from firms that do not release apps in ways that may explain our primary findings. Studying privacy actions helps mitigate these concerns because these initiatives (i) are exogenous to any one firm, (ii) are not driven by the efficiency of firms' investment and production decisions; and (iii) directly affect only firms that use mobile apps and meet certain conditions, thus providing a natural set of treatment and control firms.

First, we consider the effect of the EU's General Data Protection Regulation (GDPR), which became effective in 2018 and limited firms' ability to collect customers' confidential information. Firms affected by GDPR are required to collect only data necessary to support legitimate commercial purposes, to be transparent regarding the data collected and how it will be used, and to gain "opt-in" consent for its collection from the customer. Despite GDPR being an EU regulation, compliance is required for U.S. firms that collect or process data on EU citizens. Second, we consider a similar regulation implemented by the state of California, the California Customer Privacy Act (CCPA), which came into effect in 2020 and affected all firms with customers in the state of California. Third, we consider Privacy Nutrition Label (PNL) policies enacted by Apple's App Store in 2020 to protect customer privacy by disclosing transparently what data is collected and how it is used. We expect that firms more affected by these privacy actions will have less access to customer information from mobile apps and thus less information about customer demand. Consistent with our prediction, we find that more affected firms experienced reductions in the quality of their investing and production decisions following privacy initiatives.

Our main findings are aligned with the notion that information obtained through mobile apps leads to improved forecasts of customer demand and thus more efficient investing and

production decisions. However, these results may also be consistent with mobile apps resulting in more stable consumer demand because they increase customer engagement and retention, which leads to a more stable revenue stream. For this reason, we next study whether firms that adopt mobile apps (i) experience more stable demand, as proxied by revenue volatility and persistence; and (ii) display more accurate management forecasts of earnings and revenue. Our evidence indicates that mobile apps are not associated with more stable revenue streams, but are associated with more accurate management earnings and revenue forecasts. Jointly considered, these results suggest that firms with mobile apps benefit from superior information but not necessarily more stable demand for their products, consistent with our predictions about the value of customer data for reducing uncertainty and improving investing and production decisions.

We believe our study makes several contributions to the academic literature and informs regulators. First, we add to research on the implications of the internal information environment for managerial decision making. Prior research has shown that higher-quality internal information facilitates various managerial decisions such as tax planning, hiring, and investment (Gallemore and Labro 2015; Heitzman and Huang 2019; Ferracuti 2022; Binz, Ferracuti, and Joos 2023). We contribute to this literature by documenting that mobile apps allow managers to systematically gather customer information that is relevant to their decisions but would be otherwise difficult to collect. In this regard, our paper answers the call from Roychowdhury, Shroff, and Verdi (2019) to study whether technological improvements that allow firms to gather and process real-time information can affect firms' decision making. There is a developing literature exploring potential uses of big data, much of which has focused on the use of big data by investors rather than managers. For example, recent studies have examined the informativeness and market value of the data using satellite images, mobile GPS tracking, credit card transactions, and Twitter (Froot,

Kang, Ozik, and Sadka 2017; Zhu 2019; Kang, Stice-Lawrence, and Wong 2021; Jin, Stubben, and Ton 2023; Katona, Painter, Patatoukas, and Zeng 2024). However, managers' ability to acquire, process and use data to make decisions is a key driver of their firms' valuation and success (Farboodi and Veldkamp 2023). Our study investigates the role of big data in firms' internal information environment and operating decisions. This complements recent work by Charoenwong, Kowaleski, Kwan, and Sutherland (2023), who document that technological investments allow firms to reduce customer complaints and employee misconduct; Labro, Lang, and Omartian (2023), who document that firms' use of predictive analytics is associated with reduced delegation of decision rights to local managers and increased centralization of control over data gathering; and Liu, Qiu, Wang, and Yeung (2021) and Blankespoor, Hendricks, Piotroski, and Synn (2022), who examine the role of big data on voluntary disclosure.

Second, our findings highlight an unintended consequence of customer privacy initiatives. Recently, more and more state regulators in the U.S. are implementing data privacy laws to protect customers. Starting with California in 2020, Colorado, Connecticut, Utah, and Virginia passed customer privacy laws in 2022 (Jaworski and Schmeltzer 2022). In 2023, Delaware, Indiana, Iowa, Montana, Oregon, Tennessee, and Texas also passed customer privacy laws (Stauss and Lamont 2023). Massachusetts is considering a complete ban on the sale of customers' location data (Morris 2023). As more states are expected to follow suit, understanding the consequences of these initiatives can be informative to policymakers considering whether and how to implement new privacy laws. Prior research on the effects of GDPR and other initiatives has focused on the effect of these regulations on customer engagement (e.g., Zhao, Yildirim, and Chintagunta 2021; Aridor, Che, and Salz 2022), the cost of compliance to firms and improvements in internal information systems to better manage and safeguard customer data (Maex 2022), and negative effects on sales

revenue (Chen, Frey, and Presidente 2024). Ours is the first study we are aware of that considers the value of customer information gathered through mobile apps for investing and production decisions, as well as the negative consequences of privacy regulations on these decisions. To the extent that firms pass investing and operating efficiencies—at least partially—to customers in the form of lower prices, then customers may face higher prices when these regulations are in place. We emphasize that our results should not be interpreted as a call for regulators and other interested parties to abandon initiatives to protect customer privacy. Rather, they should be interpreted as evidence of a potential cost of privacy actions that regulators and other interested parties should weigh against the benefits of those actions when making policy decisions.

Lastly, we contribute to the literature on mobile apps, which to date has been conducted primarily in the areas of marketing and information systems research. The adoption of mobile apps has been found to increase customer acquisition (Datta, Foubert, and Van Heerde 2015), purchases (Montaguti, Neslin, and Valentini 2015; Xu, Chan, Ghose, and Han 2017), purchase returns (Narang and Shankar 2019), customer loyalty (Boyd, Kannan, and Slotegraaf 2019), social engagement (Jung Bapna, Ramaprasad, and Umyarov 2019), and revenues (Einav, Levin, Popov, and Sundaresan 2014; Chen, Liu, and Wu 2024). In the areas of accounting and finance, Carlin, Olafsson, and Pagel (2023) suggest that mobile app for a financial aggregation platform improves customer's financial decision-making, while Koo, Lee, Muslu, and Stice (2023) find that analysts rely less on public information (i.e., financial reports, conference calls, and meeting with firm management) and their forecasting quality declines when a firm they follow launches a mobile app. More related to our study, Wu (2023) shows that mobile app adoptions are associated with lower firm risk. Our paper offers a potential explanation for this finding: the collection of customer

data reduces uncertainty about customer demand and thus leads to improvements in investing and production decisions.

These contributions notwithstanding, we acknowledge that our evidence is inherently incomplete. While we document not only an average effect of mobile apps on managerial decision making but also additional evidence from cross-sectional tests, we leave it to future research to paint a more complete picture of the conditions under which data collected through mobile apps is useful for managerial decision making, and the full range of its uses.

II. BACKGROUND AND HYPOTHESIS DEVELOPMENT

Institutional Background

Prior to the introduction of e-commerce, retailers had relatively few means to acquire detailed information about their customers.[1] Mobile apps significantly changed this situation by creating new opportunities for firms to collect customer information. Following the release of the iPhone in 2007, Apple opened the App Store on July 10, 2008, with 500 mobile apps available. In less than one week, iPhone users had downloaded more than 10 million apps (Apple 2008). Following closely, Google launched its own mobile app platform, Android Market (now Google Play), on October 22, 2008. By 2022, the App Store and Google Play Store listed over 1.6 and 3.5 million apps, respectively. Mobile apps have become an increasingly important channel for firms to engage with and gain insights about their customers. Revenue generated through mobile apps reached $3.6 trillion worldwide in 2022, nearly three times the revenue generated just five years earlier. In the U.S., 7.4 percent of total retail sales originate from mobile apps (Curry 2024). Even customers who shop in-store frequently use mobile apps to browse products or identify discounts.

[1] For example, in the past retailers often used mail-in product warranty cards or product registration cards to gather information about their customers. However, the amount of data collected was limited and retailers had to contend with low response rates and nonresponse bias.

For example, more than half of customers have used a retailer's mobile app while shopping in-store (Mulligan 2019). As customer engagement with mobile apps increases, the quality and quantity of customer data available to firms increase as well.

Through mobile apps, firms build a direct, timely, and interactive link with their customers, which allows them to obtain extensive and high-quality information about customers and sales in real time. Similar to traditional internal information systems, mobile apps allow firms to collect and organize data to generate insights into customer demand. However, mobile apps leverage features and data collected through the user's mobile device that would be difficult or impossible to gather and analyze outside of these apps. App users are typically asked to share information in exchange for a better app experience, which can include the device identifier, GPS location, personal information (e.g., contacts, call log, calendar, photos, and fingerprints), and financial information (e.g., purchase and payment history). Using the device ID, firms can acquire and link data collected by other apps.[2] In summary, mobile apps allow firms to gather granular customer information in real time that would be otherwise difficult to collect from other sources.

Main Predictions

The customer information collected from mobile apps can help managers not only to increase their sales but also to forecast future sales more accurately. Thus, we expect mobile apps to help managers make superior investing and production decisions, and restrictions on information collected through those apps to hurt investing and production efficiency.

Corporate Decision Making

[2] Effective April 2021, Apple implemented App Tracking Transparency (ATT), a privacy policy that requires apps to request users' permission to track them or access their device's advertising identifier.

Future demand for the firm's products and services is a key input into capital investment decisions. For example, if expected demand is high, a manager may increase capital investment to expand production capacity for existing products, enter new territories, or introduce new products. These responses to expected demand are muted in the presence of uncertainty because managers adopt a wait-and-see strategy in which they invest less and delay their (irreversible) commitments, reducing the efficiency of their investment decisions (Bernanke 1983, Bloom, Stephen, and Van Reenen 2007). To the extent that this uncertainty emanates at least partially from managers' incomplete information (Ferracuti and Stubben 2019), the adoption of mobile apps can help managers reduce uncertainty about future demand and facilitate their investment decision making.

H1: The release of a mobile app is associated with higher investment efficiency.

Uncertainty about expected demand influences not only managers' investment, but also their production decisions. Firms hold more inventory in the presence of heightened uncertainty. Uncertainty increases the likelihood of experiencing costly stock-outs in case of unexpected demand (Rubin 1980; Bo 2001; Caglayan, Maioli, and Mateut 2012), which managers must trade off against inventory holding costs. If the data collected by mobile apps allows managers to more accurately forecast demand, then inventory levels can be managed more efficiently.

H2: The release of a mobile app is associated with higher inventory efficiency.

Despite these predictions, it is possible that the release of a mobile app is not associated with improvements in investing and production decisions. For example, customer data collected through mobile apps may remain siloed in large, complex organizations. In the Zendesk Customer Experience Trends Report 2023, only 22 percent of business leaders responded that their teams share data effectively (Grieve 2023). Further, if the data is not collected with investing and production decisions in mind, it may not be of use in these decisions, especially when other sources

of data are available. It is also possible that only certain types of customer data have value outside of marketing decisions and initiatives, or that consumers provide incorrect personal information because they do not want to be targeted by marketing efforts and/or they want to protect own private information (Chahal 2015).

Moreover, the benefits of mobile apps may materialize only under the right circumstances. For instance, Charoenwong, Kowaleski, Kwan, and Sutherland (2023) discuss how adopting new technologies may require firms to have adequate information systems in place. Companies may lack strong data infrastructure or the controls needed to make sure the technology is used safely, as discussed in recent interviews with the popular press by Julie Sweet, CEO of Accenture (Foley 2023). Accordingly, if firms' information systems are inadequate, the benefits of mobile apps for investing and production decisions will remain unrealized. Relatedly, the benefits of mobile apps are likely to vary with economic conditions. For example, the information that can be produced from mobile app data may be more valuable in the presence of higher competition (Grenadier 2002) and during economic downturns (Kacperczyk, Nieuwerburgh, and Veldkamp 2016; Loh and Stulz 2018). For these reasons, we perform supplementary tests that examine the quality of internal information systems, the types of data that mobile apps collect, and various economic conditions.

Privacy Initiatives

With the dramatic increase in the amount of customer data collected by firms, customer privacy has become an important issue for customer advocates and politicians. In response, regulators and app stores have taken actions to protect customer privacy. For instance, state regulators in the U.S. have passed various data privacy laws to protect customers. California, passed customer privacy laws in 2020, while Colorado, Connecticut, Utah, and Virginia passed similar laws in 2022 (Jaworski and Schmeltzer 2022). In 2023, Delaware, Indiana, Iowa, Montana,

Oregon, Tennessee, and Texas also passed customer privacy laws (Stauss and Lamont 2023), while Massachusetts is considering a complete ban on the sale of customers' location data (Morris 2023).

An implication of our predictions is that when firms are limited in the customer information they can gather with mobile apps, as intended by the privacy initiatives discussed above and other similar initiatives, their investing and production decisions may become less efficient. Accordingly, we make the following hypothesis:

H3: Investment and inventory efficiency decrease following privacy initiatives.

III. SAMPLE AND VARIABLES

Sample

We test our hypotheses using a sample that combines mobile app data from Appfigures, accounting data from Compustat, stock market data from CRSP, management forecast data from Thomson/Refinitiv, and institutional ownership data from Thomson Reuters. We obtain release dates, features, and the developer for mobile apps on Apple App Store and Google Play from Appfigures, restricting our sample to apps operated in the U.S. with English as the primary language. We link this information to Compustat using a Python crawling technique that identifies the types of user data collected as well as the name of app developers of individual apps. We match the app developer name to Compustat company names using a fuzzy matching algorithm. The algorithm can match multiple apps to each firm. For example, our algorithm matches Amazon with Amazon Prime Video, Amazon Kindle, Amazon Music, and subsidiary apps such as Whole Foods.

Our sample begins in 2006, which is two years before the first app release, and ends in 2021, which is the most recent year available on Compustat at the time of data collection. We exclude observations with total assets less than $1 million and retain only firms in Global Industry Classification (GIC) six-digit industries with at least 10 percent of firms that have launched mobile

shopping apps at any point during the sample period. The latter restriction is necessary because some industries such as Mining and Railroads rarely use mobile apps for business purposes. We also exclude financial industries (two-digit GIC = 40) and require non-missing data to calculate variables included in our main analyses, which results in a final sample of 28,655 firm-year observations, distributed among 3,491 firms for the period 2006-2021. Some analyses include fewer observations due to additional data requirements.

Measurement of Key Variables

The key variables in our study are firms' mobile app adoption and the efficiency of both investment and inventory management. We measure firms' mobile app adoption as *App Launch*, an indicator set to one in the year of or years following the initial mobile app launch, and zero prior to the app launch. We use the date of the first app release for firms with multiple apps.

Investment efficiency is inherently difficult to measure. Accordingly, we use several commonly used proxies, each with its own strengths and weaknesses (Roychowdhury, Shroff, and Verdi 2019). We measure investment efficiency using unexplained investment in our main analyses, and investment sensitivity to growth opportunities, total factor productivity, and return on assets in robustness tests. Following McNichols and Stubben (2008), we calculate unexplained investment using the absolute value of the residuals from the following regression model, estimated by industry and year:

$$\begin{aligned} Investment_{it} = {} & \beta_0 + \beta_1 Tobin's\ Q_{it-1} + \beta_2 Tobin's\ Q_{it-1} \times Quartile2_{it-1} \\ & + \beta_3 Tobin's\ Q_{it-1} \times Quartile3_{it-1} + \beta_4 Tobin's\ Q_{it-1} \times Quartile4_{it-1} \\ & + \beta_5 CF_{it} + \beta_6 Growth_{it-1} + \beta_7 Investment_{it-1} + \varepsilon_{it}, \end{aligned} \quad (1)$$

where $Investment_{it}$ is capital expenditures scaled by the beginning-of-year net property, plant, and equipment (PP&E). $Tobin's\ Q_{it-1}$ is market value of equity plus total assets minus book value of equity, scaled by the total assets. $Quartile2_{it-1}$, $Quartile3_{it-1}$, and $Quartile4_{it-1}$ are indicator variables equal to one if Tobin's Q belongs to the second, third, and fourth quartile of the industry-year

distribution, respectively, which allows for nonlinearity in the association between Tobin's Q and investment. CF_t is cash flow from operations scaled by beginning net PP&E. $Growth_{it-1}$ is natural logarithm of total assets in year *t-1* scaled by total assets in year *t-2*. We estimate Equation (1) by GIC six-digit-year group and require each group to include at least 10 observations. We measure investment inefficiency using the absolute value of residuals ($|Abnormal\ Investment_{it}|$), namely the portion of investments unexplained by firms' growth opportunities. Lower values of this variable indicate higher investment efficiency.

Finally, we measure the efficiency of production decisions using inventory turnover ($Inventory\ Turnover_{it}$). We calculate this variable as cost of goods sold scaled by the average inventory during the fiscal year. Given the highly skewed distribution of this ratio, we use its logarithmic transformation in our analyses.

Descriptive Statistics

Table 1 presents descriptive statistics for our sample, where all continuous variables are winsorized at the 2nd and 98th percentiles. Panel A shows that that 14 percent of firm-year observations have launched an app. Panel B reveals that the mean of *App Launch* increases from 0 to 33 percent throughout the sample period, while Panel C documents substantial variation in mobile app adoption both within and across two-digit GIC industries. At a more granular six-digit GIC level, Interactive Media & Services (36.6 percent), Automobiles (33.9 percent), Internet & Direct Marketing Retail (33.8 percent), Airlines (31.4 percent), and Entertainment (31.2 percent) industries have the highest means of *App Launch*, while Health Care Providers & Services (3.7 percent), Commercial Services & Supplies (3.8 percent), and Water Utilities (4.1 percent) have the lowest means of *App Launch*. Finally, we present the Pearson correlation matrix of key variables used in the regressions in Table 2. The table shows that *App Launch* is negatively associated with

the absolute value of abnormal investments (coeff. = -0.01) and positively associated with inventory turnover (coeff. = 0.05), lending preliminary support to our hypotheses.

IV. RESEARCH DESIGN AND EMPIRICAL RESULTS

Investment Efficiency Following the Launch of a Mobile App

We test our prediction that the release of a mobile app is associated with higher investment efficiency by estimating the following OLS regression:

$$|Abnormal\ Investment_{it}| = \beta_0 + \beta_1 App\ Launch_{it} + Controls + Firm\ fixed\ effects + Year\ fixed\ effects + \varepsilon_{it}, \quad (2)$$

where $|Abnormal\ Investment_{it}|$ and $App\ Launch_{it}$, are defined as previously. We follow prior literature (i.e., Chen, Hope, Li, and Wang 2011; Cohen and Li 2020) and include as controls the natural log of total assets ($Assets_{it}$); the natural log of the number of years since the firm's first appearance in the Compustat database (Age_{it}); total debt scaled by total assets ($Leverage_{it}$); the number of sell-side analysts that issued a forecast during the year ($\#Analysts_{it}$); the fraction of shares outstanding held by institutional investors ($\%Institutional_{it}$); the standard deviation of revenue (scaled by assets) over the previous twelve quarters ($Revenue\ Volatility_{it}$); and revenue scaled by assets ($Asset\ Turnover_{it}$). We include firm fixed effects to absorb time-invariant firm characteristics and year fixed effects to absorb firm-invariant but year-specific variation in abnormal investment over time. Standard errors are clustered by firm.

Under H1, we expect to observe a positive association between investment efficiency and the release of a mobile app, which predicts a negative estimated β_1 coefficient. Table 3, which reports our coefficient estimates for Equation (2), lends empirical support to this prediction: in Column (1), the estimated coefficient on $App\ Launch_{it}$ is negative and statistically significant (coeff. = -0.046, t-stat = -1.86), indicating higher investment efficiency following the release of a

mobile app. In economic terms, the initial release of a mobile app is associated with a 5 percent standard deviation decrease in $|Abnormal\ Investment_{it}|$, which amounts to 5 percent of net PP&E.

We next explore whether this association is driven by increases in investments by underinvesting firms, decreases in investment by overinvesting firms, or a combination of the two. To do so, we re-estimate Equation (2) separately for firms with positive (i.e., overinvesting) and negative (i.e., underinvesting) unexplained investment, and report estimated coefficients in Columns (2) and (3), respectively. We document that the launch of a mobile app is associated with lower underinvestment but not with overinvestment, as indicated by negative and significant coefficient in Column (3) (coeff. = -0.082, t-stat = -2.36) and insignificant coefficient in Column (2) (coeff. = 0.037, t-stat = 0.98). This evidence suggests that mobile app adoption helps managers mitigate information uncertainty and therefore reduces the underinvestment that results from a wait-and-see strategy in the face of uncertainty about consumer demand.

Our baseline analysis is similar in spirit to a staggered difference-in-differences design, in which some firms are treated (i.e., they adopt a mobile app) at different times and some firms are never treated (i.e., they never adopt a mobile app).[3] Recent research indicates that staggered designs can produce invalid estimates with heterogeneous or trending treatment effects because of the inclusion of previously treated units as controls (Barrios 2022; Baker, Larcker, and Wang 2022). Accordingly, we follow the literature (e.g., Cengiz, Dube, Lindner, and Zipperer 2019) and assess the robustness of our findings to a stacked regression approach. We construct a cohort of firms that launch a mobile app in the same year, and we create two control groups: one that comprises a combination of firms that have never adopted mobile apps during the sample period

[3] Our approach is similar in spirit but not in substance to a staggered difference-in-differences design because the treatment status is not exogenous but instead reflects firms' selection into it.

or that adopt mobile apps in the later periods, and one exclusively with firms that have never adopted mobile apps during the sample period. We then stack all cohort datasets together and estimate Equation (2) on this new database, replacing firm and year fixed effects with cohort-firm and cohort-year fixed effects to control for time-invariant firm characteristics and secular time trend for different cohorts (Gormley, Matsa, and Milbourn 2013).[4] The results presented in Columns (4) and (5) of Table 3 support our baseline findings: the estimated coefficient continues to be negative, economically meaningful and statistically significant.

Inventory Management Following the Launch of a Mobile App

We next test whether the quality of managers' inventory management is positively associated with the release of a mobile app with the following OLS regression:

$$\begin{aligned} \textit{Inventory Turnover}_{it} = {} & \beta_0 + \beta_1 \textit{App Launch}_{it} + \textit{Controls} \\ & + \textit{Firm fixed effects} + \textit{Year fixed effects} + \varepsilon_{it}, \end{aligned} \tag{3}$$

where $\textit{Inventory Turnover}_{it}$ and $\textit{App Launch}_{it}$, are as defined previously. Following the literature (i.e., Feng, Li, McVay, and Skaife 2015), we include as controls the natural log of total assets ($\textit{Assets}_{it}$); the natural log of the number of years since the firm's first appearance in the Compustat database ($\textit{Age}_{it}$); sales minus cost of sales scaled by sales ($\textit{Gross Margin}_{it}$); the natural logarithm of gross property, plant, and equipment ($\textit{Capital Intensity}_{it}$), the standard deviation of revenue (scaled by assets) over the previous twelve quarters ($\textit{Revenue Volatility}_{it}$); sales less lagged sales scaled by lagged sales ($\textit{Revenue Growth}_{it}$); the number of geographic and operating segments ($\textit{Segments}_{it}$); an indicator equal to one if the firm reports foreign sales ($\textit{Foreign Sales}_{it}$), earnings before extraordinary items scaled by average total assets ($\textit{ROA}_{it}$); an indicator equal to one if the firm has a Big-Four auditor ($\textit{Big-4 Auditor}_{it}$); and an indicator equal to one if the firm reports

[4] Results are qualitatively similar if we limit the window to 2 or 3 years around the event.

negative net income ($Loss_{it}$). As with Equation (2), we include firm and year fixed effects and cluster standard errors by firm.

Under H2, we expect that inventory efficiency is positively associated with the release of a mobile app, which predicts a positive estimated β_1 coefficient. Table 4 presents the estimation results of Equation (3) and lends support to our hypothesis. In Column (1), β_1 is positive and significant (coeff. = 0.043, t-stat = 1.98), indicating that the launch of a mobile app is associated with a 4 percent increase in inventory turnover.[5] We also find that this increase extends from higher inventory turnover for raw materials (coeff. = 0.198, t-stat = 2.87) and finished goods (coeff. = 0.113, t-stat = 2.02), but not work-in-process (coeff. = -0.020, t-stat = -0.19).

We then repeat this analysis using a stacked regression approach, where the database is constructed as it was for Columns (4) and (5) of Table 3. Columns (5) and (6) of Table 4, which report the stacked coefficient estimators, support our baseline findings—the coefficient is positive, and both the economic magnitude and statistical significance increase, suggesting that our findings are not driven by bias in our estimates.

Taken together, the evidence presented in Tables 3 and 4 is consistent with mobile apps being associated with improved investment efficiency, primarily by reducing underinvestment, and improved inventory efficiency, especially for raw materials and finished goods.[6,7]

The Effect of Privacy Initiatives

[5] These findings become stronger (coeff.: 0.059; t-stat: 2.76) when we restrict the sample to firms with greater inventory levels, i.e., industrials (two-digit GIC = 20), customer discretionary (two-digit GIC = 25) and customer staples (two-digit GIC = 30).

[6] Untabulated findings reveal that these results are robust to alternative definitions of mobile app adoption, including the number of ratings received, and to alternative industry definitions. Further, the investment results are robust to (i) estimating a single-step quantile regression as an alternative to Equation (2), as recommended by Chen, Hribar, and Melessa (2023), and (ii) proxying for investment efficiency with the responsiveness of investment to growth opportunities, return on assets, or total factor productivity calculated following Hann. Kim, Wang, and Zheng (2020).

[7] Untabulated findings indicate that these results are robust to excluding the year of the app launch.

The amount of data collected on customers has dramatically increased in recent years, putting customer privacy at the center of discussions of customer advocates and politicians and leading to initiatives by regulators and app stores to protect customer privacy. These initiatives have combined to limit the amount and quality of customer information available to firms. We expect that the value of customer data collected through mobile apps for operating decisions decreases following the introduction of these initiatives because they limit the amount of customer data that companies can collect and use. We examine the effects of three such privacy initiatives: the European Union's General Data Protection Regulation (GDPR), the California Customer Privacy Act (CCPA), and the Apple Store's Privacy Nutrition Label (PNL) requirements.

We do so by using a difference-in-differences approach. More specifically, for each privacy action, we identify a treatment group of firms that were more significantly affected by the action and a control group of firms that were less or not affected by the action. We then estimate the following regression specification on three separate samples:

$$Y_{it} = \beta_0 + \beta_1 Affected_i \times Post_t + Controls + Firm\ fixed\ effects + Year\ fixed\ effects + \varepsilon_{it,} \quad (4)$$

where Y_{it} is either $|Abnormal\ Investment_{it}|$ or $Inventory\ Turnover_{it}$. $Affected_i$ identifies our treatment firms, i.e., firms with greater exposure to the consequences of privacy actions, and $Post_t$ identifies the post-privacy-action period. To help ensure control groups are similar to the treatment groups except for the effect of the privacy action, we exclude firms that have not yet adopted a mobile app by the start of the sample period. Further, to reduce the risk that our analyses are contaminated by other events, we restrict the sample period to 2015 forward for GDPR and 2018 forward for CCPA and PNL. Control variables, fixed effects, and standard error clustering are the same as in Equations (2) and (3). The main effects of $Affected_t$ and $Post_t$ are dropped because they are absorbed by firm and year fixed effects, respectively. We expect that as a byproduct of a reduced ability to collect and use customer information, affected firms experience a relative

decline in investment and inventory efficiency following each of these three privacy initiatives. Thus, we expect to observe a positive (negative) estimated β_1 coefficient when the outcome variable is abnormal investment (inventory turnover).

These tests are interesting on their own right, but they also help mitigate concerns that our findings in Tables 3 and 4 are driven by firms' selection into mobile app adoption. The adoption of GDPR, CCPA, and PNL was largely outside of firms' control and independent of the investing and production decisions of those firms, thus helping us to rule out endogenous factors associated with mobile app use, and to make stronger conclusions about the *causal* effect of mobile apps on firms' internal information environments and decision making.

General Data Protection Regulation

On May 25, 2018, the European Union's General Data Protection Regulation (GDPR) became effective. GDPR limited firms' ability to collect EU citizen app users' confidential information. Firms that collect or process data on EU citizens (U.S. firms included) are required to collect only data necessary to support legitimate commercial purposes, to be transparent regarding the data collected and how it will be used, and to gain "opt-in" consent for its collection.[8] Research on GDPR has documented negative effects on customer data sharing (Johnson, Shriver, and Goldberg 2024), web traffic and e-commerce sales (Aridor, Che, and Salz 2022, Goldberg, Johnson, and Shriver 2024), and total sales and profitability (Chen, Frey, and Presidente 2024).

We test our hypothesis that GDPR also resulted in less efficient investing and production decisions by estimating Equation (4) above. We define *Affected* as *HighEU%*, an indicator set to one if the percentage of the app's total downloads that occurred in the EU is above the sample

[8] Maex (2022) finds that 29 percent of U.S. firms reference GDPR among their 10-K risk factors. The consequences of violating GDPR are potentially large. For example, in December 2020, Google and Amazon were fined $120M and $42M, respectively, by French authorities for loading tracking cookies onto users' computers when visiting their websites in a manner that violated GDPR (Lomas 2020).

median, and zero otherwise; and *Post* as an indicator set to one if the firm's fiscal year-end is after the GDPR enforcement date (May 25, 2018), and zero otherwise. The coefficient of interest is $\beta_{1,}$ which captures the incremental effect of GDPR on affected firms (i.e., firms with relatively more mobile app use in EU countries) over that of control firms (i.e., firms with relatively less or no mobile app use in EU countries). We predict a positive (negative) coefficient for |*Abnormal Investment*| (*Inventory Turnover*), consistent with the argument that firms with reduced access to customer information from mobile apps following the enforcement of GDPR experience declines in investment and production efficiency.

The findings presented in Table 5, Panel A, Columns (1) and (2), support our hypothesis. Firms with relatively more exposure to GDPR exhibit an increase in unexplained investment (Column (1): coeff. = 0.146, t-stat = 2.33) and a decrease in inventory turnover (Column (2): coeff. = -0.116, t-stat = -2.45) relative to firms with relatively less exposure to GDPR. The coefficient estimates suggest that affected firms experience a relative increase in unexplained investments of 15 percent and a relative decrease in inventory turnover of 12 percent.

California Customer Privacy Act

The state of California implemented a regulation similar to GDPR, the California Customer Privacy Act (CCPA), which was enforced beginning July 1, 2020. CCPA requires that firms disclose to customers what personal data is being collected and how it is used, and it allows customers to prohibit the sale of personal data or to request the data to be deleted. The regulation extends to any firm that does business in California and meets one of the following three thresholds: annual gross revenues of $25 million, collection of personal information of at least 50,000 customers, or more than half of revenue from selling customers' personal information.

We test our hypothesis that CCPA resulted in less efficient investing and production decisions by estimating Equation (4) above. We define *Affected* as *California*, an indicator set to

one if the firm's business address is located in California, and zero otherwise, and *Post* as an indicator set to one if the firm's fiscal year-end is after the CCPA enforcement date (July 1, 2020), and zero otherwise.[9] The coefficient of interest is $\beta_{1,}$ which captures the incremental effect of CCPA on firms with a mobile app that are located in California.

As reported in Columns (3) and (4) of Table 5, firms with a mobile app located in California exhibit a relative increase in abnormal investment of 58 percent (Column (3): coeff. = 0.576, t-stat = 1.84) following the enforcement of the CCPA, and a relative decrease in inventory turnover of 11 percent (Column (4): coeff. = -0.109, t-stat = -1.91).

Privacy Nutrition Labels

In addition to regulators, app stores have also recently taken steps to protect customer privacy. For example, Apple's App Store has enacted Privacy Nutrition Label (PNL) policies to protect customers.[10] These app stores require app developers to disclose what data is collected and how it is used. We test our hypothesis that Apple's PNL disclosures resulted in less efficient investing and production decisions by estimating Equation (4) above. We define *Affected* as *High#Data_Apple*, an indicator set to one for firms with apps that that collect or share customer data above the median in Apple's App Store, and zero otherwise; and *Post* with an indicator variable that equals one if the firm's fiscal year-end is after Apple's App Store PNL requirements became effective (December 8, 2020), zero otherwise.

Consistent with our hypotheses, Table 5 reveals that firms that collect an above-median amount of data through their mobile apps in Apple Store experience a relative increase in abnormal

[9] We do not observe the exact locations where firms generate revenues. For this reason, we rely on the assumption that firms generate the majority of their revenues in the state of their business address. If this assumption is violated, then we identify affected firms imprecisely and introduce attenuation bias (via measurement error) in our estimations.
[10] Google Play Store has also enacted similar policies. We do not examine Google Play Store's policies because they were enacted late in our sample period, and therefore we do not observe a long enough post-implementation period.

investment (Column (5): coeff. = 0.194, t-stat = 2.83) and a relative decrease in inventory turnover (Column (6): coeff. = -0.087, t-stat = -1.99). These effects are economically significant: abnormal investment increases by 19 percent and inventory turnover declines by 9 percent.

Taken together, our evidence suggests that privacy initiatives, which are intended to protect customers, produce the unintended effect of reducing the efficiency of firms' investing and production decisions by limiting the amount and quality of information available to firms.[11]

V. ADDITIONAL ANALYSES

Why Do Mobile Apps Help? Better Information versus More Stable Demand

While we predict that mobile apps are associated with higher investment and inventory efficiency because they allow managers to better forecasts future demand (i.e., the information channel), mobile apps may also help to shape customer behavior in a way that makes future demand more predictable (i.e., the demand channel). Clearly separating the two channels is difficult because they are interwoven and endogenously determined. Thus, in this section we search for evidence to support either or both channels. We start by studying whether firms that introduce mobile apps experience more stable and persistent revenues, which would indicate the existence of a demand channel. To do so, we estimate the following OLS regression:

$$Y_{it+1} = \beta_0 + \beta_1 App\ Launch_{it} (+ \beta_2 Revenue_{it} + \beta_3 App\ Launch_{it} \times Revenue_{it}) + Controls + Firm\ fixed\ effects + Year\ fixed\ effects + \varepsilon_{it}, \quad (5)$$

where Y_{it+1} is a place holder for $Revenue\ Volatility_{it+1}$, the standard deviation of revenues over the following three years, or $Revenue_{it+1}$, revenues in year $t+1$ scaled by revenue in year t. We use the same controls as in Equation (2), as well as firm and year fixed effects.

[11] We find qualitatively similar results when we exclude the year of the privacy initiative (i.e., 2018 for GDPR, and 2020 for CCPA and Apple's privacy nutrition labels).

If mobile apps make demand more stable or predictable, we expect: (i) a negative β_1 coefficient when the outcome variable is *Revenue Volatility*$_{it+1}$, which indicates that mobile app adoption is associated with less volatile consumer demand; and (ii) a positive β_3 coefficient when the outcome variable is *Revenue*$_{it+1}$, which indicates that mobile app adoption is associated with more persistent revenues. We report estimated coefficients in the first two columns of Table 6. We fail to detect a statistically significant decrease in revenue volatility (Column (1): coeff. = 0.007, t-stat = 1.52) or increase in revenue persistence (Column (2): coeff. = -0.045, t-stat = -0.62). This evidence indicates that the introduction of a mobile app is not associated with a statistically significant change in the stability of demand.

We next examine whether firms that adopt mobile apps experience lower information uncertainty, measured as improved management forecast accuracy. We estimate the following OLS regression on 5,552 firm-year observations with management earnings and revenue forecasts:

$$\begin{aligned} \textit{Management Forecast Accuracy}_{it} = {} & \beta_0 + \beta_1 \textit{App Launch}_{it} + \textit{Controls} \\ & + \textit{Firm fixed effects} + \textit{Year fixed effects} + \varepsilon_{it}, \end{aligned} \tag{6}$$

Management Forecast Accuracy$_{it}$ is a placeholder for either |*Earnings Forecast Error*$_{it}$|, the absolute value of the difference between actual and forecasted earnings per share for the year scaled by stock price at the beginning of year *t*, or |*Revenue Forecast Error*$_{it}$|, the absolute value of the difference between actual sales revenue and forecasted revenue for the year scaled by the market value of equity at the beginning of year *t*. All forecasts are initial forecasts for the forecasting period. *Controls* is a vector of important determinants of management forecast accuracy (Koo and Lee 2018). Importantly, we include proxies for fundamental volatility such as sales and stock return volatility to hold fundamental uncertainty (to the extent captured by our controls) constant. We also include firm fixed effects and year fixed effects to absorb time-invariant firm characteristics and variation over time, and cluster standard errors by firm.

Our estimates, reported in the last two columns of Table 6, show that management forecast accuracy is positively associated with the launch of a mobile shopping app—both earnings forecast errors (Column (3): coeff. = -0.011, t-stat = -2.32) and revenue forecast errors (Column (4): coeff. = -0.014, t-stat = -1.68) are lower for firms with a mobile app.

The evidence in this section suggests that firms that release mobile apps experience lower information uncertainty but not lower fundamental uncertainty. Thus, our main findings are likely driven by the information channel, as posited in our hypotheses.

Under What Conditions Do Mobile Apps Help?

In the previous sections, we have documented that mobile apps help firms make superior investing and production decisions, and that this effect likely results from an information channel. Because the benefits of mobile app adoptions are possibly heterogeneous across firms and over time, in this section we study under which conditions these benefits arise.

Internal Information System Quality

Advanced technological solutions such as mobile apps may require richer databases and better cybersecurity, app development, and overall technological infrastructure (Charoenwong, Kowaleski, Kwan, and Sutherland 2023). Absent this infrastructure, the firm may lack the tools necessary to leverage the information provided by apps for investing and production decisions. Not only does the customer data need to be collected and analyzed, but it also must be transmitted within the organization to those who make investing and production decisions. Yet, Grieve (2023) finds that only 22 percent of business leaders indicate that their teams share data effectively. Finally, because mobile apps are considered primarily as marketing tools (Stocchi, Pourazad, Michaelidou, Tanusondjaja, and Harrigan 2021; Watson, McCarthy, and Rowley 2013), some managers may not be aware of the potential uses and benefits of the customer data that is collected. For these reasons, we expect firms with superior internal information systems to be more likely to use

customer data collected from mobile apps not just marketing decisions but also for investing and production decisions.

We test this conjecture by re-estimating Equations (2) and (3) separately for firms with high and low internal information system quality. To do so, we identify firms with high internal information system quality in two ways: whether the firm in included in *InformationWeek*'s list, which ranks the top 500 information technology firms; and whether the firm has a Chief Information Officer or Chief Technology Officer on its board of directors.[12] We report coefficient estimates in Table 7, Panel A. The table shows that for firms with high information system quality, mobile app adoption is associated with lower abnormal investment (Column (1): coeff. = -0.161, t-stat = -2.02; Column (5): coeff. = -0.054, t-stat = -1.69) and higher inventory turnover (Column (3): coeff. = 0.124, t-stat = 2.06; Column (7): coeff. = 0.047, t-stat = 1.72). At the same time, we do not find any significant association between abnormal investment and inventory turnover and app adoption for firms with lower information system quality. Furthermore, the difference in coefficients across the two subsamples is statistically significant at conventional significance levels, with the exclusion of abnormal investment when measuring internal information system quality with CIO or CTO. Collectively, the results are broadly consistent with firms with superior information system quality benefiting more from the launch of mobile apps.

Economic Conditions

A general principle in decision theory is that information acquisition is more valuable when outcomes are more uncertain (Kacperczyk, Nieuwerburgh, and Veldkamp 2016). Thus, we study

[12] We thank Brooke Beyer and Eric Rapley for sharing with us their data on *InformationWeek* rankings. As they discuss in Abernathy, Beyer, Downes, and Rapley (2020), this ranking is used in a number of studies as a measure of IT quality, as it captures firms with a superior investment in and utilization of information technology.

whether the benefits of mobile app adoption are larger in two sources of cross-sectional and time-series variation in outcome uncertainty—product market competition and industry shocks.

As discussed by Stigler (1963), competitive industries should experience more volatile cash flows because competition is associated with diminishing marginal returns on both new and existing assets. Consistent with these arguments, empirical evidence indicates that more competitive industries experience more volatile (Lev 1983) and less persistent (Li, Lundholm, and Minnis 2013) earnings. Accordingly, we expect that the benefits of mobile app adoption are larger for firms in more competitive industries because these firms face more uncertain demand streams. We test this prediction by estimating Equations (2) and (3) on subsamples of firms with high or low product market competition. Following Li (2010), we measure product market competition as a common factor underlying the covariance among the variables Herfindahl-Herschman Index, four-firm concentration ratio, industry size, and total number of firms in an industry, obtained through principal component analysis, and identify high product market competition when this variable falls below the sample median. Table 7, Panel B, which reports the associated estimates in Columns (1) to (4), lends support to our expectation: firms with mobile apps operating in industries with high product market competition exhibit lower abnormal investment (Column (1): coeff. = -0.125, t-stat = -2.37) and higher inventory turnover (Column (3): coeff. = 0.077, t-stat = 2.32). We do not find significant associations between mobile apps and either abnormal investment (Column (2): coeff. = -0.006, t-stat = -0.22) or inventory turnover (Column (4): coeff. = 0.016, t-stat = 0.56) for firms facing low product market competition. Further, the differences in coefficients across sub-samples are statistically different at conventional significance levels.

Both macro and micro uncertainty rise sharply during bad times (Bloom 2014). As a consequence, forecasting is harder during negative shocks (Orlik and Veldkamp 2014), which

makes information even more valuable. Accordingly, we expect that the benefits of mobile app adoption are larger for firms in industries that experience negative shocks and hence higher uncertainty about the future. We test this prediction by estimating Equations (2) and (3) on subsamples of industries that are or are not experiencing downturns, respectively. We classify industries experiencing downturns when the industry's revenue growth is the bottom 33 percent of the overall distribution of industry revenue growth (Carvalho 2015). Table 7, Panel B, which reports the estimates in Columns (5) to (8), lends support to our expectation. We find that firms with mobile apps in industries facing economic downturns exhibit lower abnormal investment (Column (5): coeff. = -0.046, t-stat = -1.73) and higher inventory turnover (Column (7): coeff. = 0.035, t-stat = 1.83). We do not find significant associations between mobile apps and either abnormal investment (Column (6): coeff. = 0.011, t-stat = 0.27) or inventory turnover (Column (8): coeff. = 0.024, t-stat = 0.82) for firms in industries that are not experiencing downturns. Further, the differences in coefficients across sub-samples are statistically different at conventional significance levels.

Overall, the evidence in this section indicates that the information benefits of mobile apps are larger when firms face more uncertain customer demand.

How Do Mobile Apps Help?

Having studied why and when mobile apps are associated with managers' superior decisions, we then investigate which app features are most beneficial. We start by investigating whether the benefits are larger for mobile apps that allow greater acquisition of customer information. This test also allows us to alleviate the concern that some mobile apps are merely add-ons that do not collect customer information. To do so, we expand Equations (2) and (3) by adding the interaction between *App Launch* and $High\#SDK_{it}$, an indicator set to one for apps with

a higher-than-average number of software development kits, and zero otherwise. These kits are packages that contain tools which allow for the collection of more and higher-quality information, among other features. Consistent with this notion, we find in Table 8, Panel A that the effect of mobile apps on both investment and inventory efficiency is concentrated among apps with higher-than-median number of software development kits.

We then conduct an exploratory analysis to understand which sources and types of customer information inform investing and production decisions. We replace *App Launch* with five different indicators set to one if the firm has at least one app that collects customers' location ($Location_{it}$), contact information such as e-mail address or phone number ($Contact_{it}$), identity ($Personal_{it}$), financial information such as purchase and payment history ($Financial_{it}$), and search history ($Search_{it}$), respectively. Table 8, Panel B reports the results from this investigation. We find that abnormal investment is negatively associated with the launch of apps that collect customers' location or financial information (Column (1)). We also find that inventory turnover is positively associated with the launch of apps that collect customers' financial information (Column (2)). These findings do not imply that only location and financial information is important to investment and production decisions; it is possible that these are the types of useful information that is newly available through mobile apps and not available elsewhere.

How Quickly Do Mobile Apps Help?

Although the availability of customer data from mobile apps can be immediate, it may take time for the firm to acquire enough customer data to be useful, and process and share that data with the appropriate decision makers within the organization. To explore the speed in which mobile app adoption is associated with improvements in investment and inventory efficiency, we expand Equations (2) and (3) by adding indicator variables for the year of the app launch (*App*

Launch[0]), the year following the app launch (*App Launch[1]*), and subsequent years (*App Launch[2+]*). The results presented in Table 9 reveal that while the launch of mobile apps is immediately associated with higher inventory efficiency (Column (2): *App Launch[0]* coeff. = 0.030, t-stat = 1.85), the relation with capital investment efficiency is delayed by at least two years (Column (1): *App Launch[2+]* coeff. = -0.075, t-stat = -3.33). These findings are consistent with the nature of those two decisions: inventory management has shorter horizon than investment.

VI. CONCLUSION

Firms' success depends heavily on managers' ability to understand customers. As such, information about customers can represent a key ingredient to firms' decision-making processes and ultimately profitability. In this paper, we investigate whether recent technologies that facilitate the collection of customer information for marketing purposes—mobile apps—also facilitate investing and production decisions, and whether privacy initiatives intended to protect customers restrict firms' ability to access these efficiency gains.

Our evidence indicates that mobile apps, which are an increasingly important channel by which firms interact with and learn about their customers, are associated with more efficient investment and production decisions. This is particularly true for firms that have effective internal information systems and for firms that collect location data and financial information of their customers. We also document that these efficiency gains are muted after the enactment of regulatory or private initiatives intended to protect customer privacy.

We believe that our evidence can provide important insights to both researchers and regulators. First, we contribute to research on the implications of the internal information environment for managerial decision making. We show that mobile shopping apps allow managers to systematically gather information that is relevant to their decisions but would be otherwise

difficult to collect, which speaks to the developing literature exploring potential uses of big data. Second, we show that customer privacy initiatives can produce the unintended consequence of reducing the amount and quality of information available to firms when making investing and production decisions—information that facilitates efficient decision making and can result in higher economic efficiency. To the extent that firms pass at least part of those efficiencies on to customers in the form of lower prices or higher-quality products and services, then customer privacy initiatives can harm the very individuals they were trying to protect. Finally, we contribute to the literature on mobile apps. While marketing and information systems literatures have examined the value of mobile apps, these literatures have not addressed the benefits of mobile apps for firms' investing and operating decision making. Our study highlights the role played by mobile apps as a venue to reduce demand uncertainty and improve the quality of firms' internal information environment and thereby their decision making.

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Appendix A
Variable Definitions

Variable	Definition
App Launch$_{it}$	Equals 1 if an app was launched in or before year *t*, and 0 otherwise.
|*Abnormal Investment*$_{it}$|	Absolute value of residual of the investment efficiency model based on McNichols and Stubben (2008). We group by GIC 6-digit industry and fiscal year to conduct the industry-year regression.
Inventory Turnover$_{it}$	Natural logarithm of the cost of goods sold scaled by average total inventory, where average total inventory is computed as the average of beginning and ending total inventory.
Inventory Turnover_RM$_{it}$	Natural logarithm of the cost of goods sold scaled by average raw material inventory, where average raw material inventory is computed as the average of beginning and ending raw material inventory.
Inventory Turnover_WIP$_{it}$	Natural logarithm of the cost of goods sold scaled by average work-in-process inventory, where average work-in-process inventory is computed as the average of beginning and ending work-in-process inventory.
Inventory Turnover_FG$_{it}$	Natural logarithm of the cost of goods soldt scaled by average finished goods inventory, where average finished goods inventory is computed as the average of beginning and ending finished goods inventory.
Assets$_{it}$	Natural logarithm of total assets.
Age$_{it}$	Natural logarithm of the number of years since the firm initially appeared in the Compustat file.
Leverage$_{it}$	Total debt, scaled by total assets.
#Analysts$_{it}$	The number of sell-side analysts that issue a forecast during year *t*.
%Institutional$_{it}$	Percentage of shares held by institutional investors from Thomson Reuters 13f Holdings Database.
Revenue Volatility$_{it}$	Standard deviation of revenue (scaled by assets) for the previous 12 quarters.
Asset Turnover$_{it}$	Total revenue scaled by total assets.
Gross Margin$_{it}$	Sales minus cost of sales scaled by sales.
Capital Intensity$_{it}$	Natural logarithm of gross property, plant, and equipment.
Revenue Growth$_{it}$	Sales less lagged sales scaled by lagged sales
Segments$_{it}$	The number of business segments.
Foreign Sales$_{it}$	Equals 1 if the firm reports foreign sales, and 0 otherwise.
ROA$_{it}$	Earnings before extraordinary items, scaled by average total asset (the mean of total assets at the beginning and end of the fiscal year)
Big-4 Auditor$_{it}$	Equals 1 if a firm has a Big-Four auditor, and 0 otherwise.
Loss$_{it}$	Equals 1 if net income is negative, and 0 otherwise.
HighEU%$_{i}$	Equals 1 if a firm has at least one app serving high number of customers in the European Union compared to the median, and 0 otherwise.
GDPR Enforcement$_{t}$	Equals 1 if firm's fiscal year-end is after the GDPR enforcement date (May 25th, 2018), and 0 otherwise.
California$_{i}$	Equals 1 if the firm's business address is located in California prior to CCPA enforcement period, and 0 otherwise.
CCPA Enforcement$_{t}$	Equals 1 if firm's fiscal year-end is after the CCPA enforcement date (July 1st, 2020), and 0 otherwise.
High#Data_Apple$_{i}$	Equals 1 if a firm has at least one app that collects or shares customer data more than the median among apps in Apple's App Store, and 0 otherwise.
Apple PNL$_{t}$	Equals 1 if firm's fiscal year-end is after the apple IOS store's privacy nutrition label (PNL) requirements became effective (December 8th, 2020), and 0 otherwise.

Revenue Volatility$_{it+1}$	Standard deviation of revenue (scaled by assets) for the following 12 quarters.
Revenue$_{it}$	Dollar revenue in year *t* scaled by dollar revenue in year *t-1*.
|*Earnings Forecast Error*$_{it}$|	The absolute value of the difference between actual and forecasted EPS, scaled by the stock price at the beginning of year *t*. All the forecasts are initial forecasts for the forecasting period.
|*Revenue Forecast Error*$_{it}$|	Absolute value of the difference between actual revenues and forecasted revenues (in thousands), converted to a per-share basis, scaled by the stock price at the beginning of year *t*. All the forecasts are initial forecasts for the forecasting period.
Earnings Forecast Horizon$_{it}$	Natural logarithm of the days between earnings forecast date and fiscal period-end date. All the forecasts are initial forecasts for the forecasting period.
Revenue Forecast Horizon$_{it}$	Natural logarithm of the days between revenue forecast date and fiscal period-end date. All the forecasts are initial forecasts for the forecasting period.
Infoweek 500$_{it}$	Equals 1 if a firm is identified as an IT leader in year *t* within the *InformationWeek* IT index, and 0 otherwise.
CIO$_{it}$	Equals 1 if a firm's chief technology officer or chief information officer is on the board (identified through BoardEx), and 0 otherwise.
Product Market Competition$_{it}$	Common factor underlying the covariance among the variables Herfindahl-Hirschman Index, four-firm concentration ratio (sum of market shares of the four largest firms in an industry), industry size (log of industry sales), and total number of firms operating in an industry, obtained through principal component analysis. The degree of product market competition is classified as High when it is below the median value, and as Low when it is above.
Industry Downturn$_{it}$	Equals 1 if an industry's revenue growth is the bottom 33% of the overall distribution of median industry revenue growth, and 0 otherwise.
High#SDKs$_{it}$	Equals 1 if a firm has at least one app with high number of software development kits (SDKs) compared to the median, and 0 otherwise.
Location$_{it}$	Equals 1 if a firm has at least one app that collects users' location, and 0 otherwise.
Contact$_{it}$	Equals 1 if a firm has at least one app that collects users' contact (e.g., e-mail address, phone number), and 0 otherwise.
Personal$_{it}$	Equals 1 if a firm has at least one app that collects users' identity (e.g., name, ID), and 0 otherwise.
Financial$_{it}$	Equals 1 if a firm has at least one app that collects users' financial information (e.g., payment, purchase), and 0 otherwise.
Search$_{it}$	Equals 1 if a firm has at least one app that collects users' search history, and 0 otherwise.
App Launch[0]$_{it}$	Equals 1 if app was released in the current year, and 0 otherwise.
App Launch[1]$_{it}$	Equals 1 if app was released in the previous year, and 0 otherwise.
App Launch[2+]$_{it}$	Equals 1 if app was released two or more years prior, and 0 otherwise.

Table 1
Descriptive Statistics

Panel A presents the descriptive statistics of variables used in the regression analysis. We restrict the sample to firms with total assets over $1 million and GIC 6-digit industries in which at least 10% of firms have launched apps. Panels B and C provide the frequency of observations and the mean of app launch indicator by fiscal year and GIC 6-digit industry, respectively. Variables are defined in Appendix A.

Panel A: Descriptive Statistics

Variable	#Obs.	Mean	Std. Dev.	p25	p50	p75
App Launch$_{it}$	28,655	0.143	0.350	0.000	0.000	0.000
|Abnormal Investment$_{it}$|	28,655	0.334	0.896	0.043	0.114	0.272
Inventory Turnover$_{it}$	20,689	2.643	1.236	1.664	2.391	3.486
Inventory Turnover_RM$_{it}$	9,682	2.283	1.857	0.000	2.513	3.593
Inventory Turnover_WIP$_{it}$	9,682	2.111	2.354	0.000	0.342	4.050
Inventory Turnover_FG$_{it}$	9,682	2.239	1.359	1.327	2.097	3.051
Assets$_{it}$	28,655	6.383	2.502	4.550	6.411	8.167
Age$_{it}$	28,655	2.907	0.649	2.485	2.890	3.332
Leverage$_{it}$	28,655	0.602	0.346	0.370	0.565	0.742
#Analysts$_{it}$	28,655	6.842	8.089	0.000	4.000	11.000
%Institutional$_{it}$	28,655	0.413	0.399	0.000	0.354	0.813
Revenue Volatility$_{it}$	28,655	0.156	0.188	0.038	0.087	0.191
Asset Turnover$_{it}$	28,655	1.079	0.764	0.493	0.871	1.484
Gross Margin$_{it}$	20,689	0.357	0.519	0.240	0.354	0.502
Capital Intensity$_{it}$	20,689	6.072	2.887	4.082	6.236	8.371
Revenue Growth$_{it}$	20,689	0.087	0.353	-0.036	0.041	0.133
Segments$_{it}$	20,689	4.211	2.798	2.000	4.000	6.000
Foreign Sales$_{it}$	20,689	0.315	0.464	0.000	0.000	1.000
ROA$_{it}$	20,689	-0.015	0.287	-0.013	0.032	0.075
Big-4 Auditor$_{it}$	20,689	0.729	0.444	0.000	1.000	1.000
Loss$_{it}$	20,689	0.277	0.448	0.000	0.000	1.000
HighEU%$_{i}$	2,388	0.645	0.479	0.000	1.000	1.000
GDPR Enforcement$_{t}$	2,388	0.560	0.497	0.000	1.000	1.000
California$_{i}$	1,792	0.218	0.413	0.000	0.000	0.000
CCPA Enforcement$_{t}$	1,792	0.512	0.500	0.000	1.000	1.000
High#Data_Apple$_{i}$	1,792	0.451	0.498	0.000	0.000	1.000
Apple PNL$_{t}$	1,792	0.512	0.500	0.000	1.000	1.000
Revenue Volatility$_{it+1}$	26,262	0.131	0.167	0.029	0.070	0.158
Revenue$_{it+1}$	28,417	0.088	0.371	-0.039	0.044	0.146
Revenue$_{it}$	28,417	0.109	0.387	-0.032	0.050	0.158
|Earnings Forecast Error$_{it}$|	5,552	0.025	0.080	0.002	0.005	0.017
|Revenue Forecast Error$_{it}$|	5,552	0.066	0.141	0.006	0.019	0.059
Earnings Forecast Horizon$_{it}$	5,552	5.136	1.421	5.069	5.743	5.793
Revenue Forecast Horizon$_{it}$	5,552	5.081	1.573	5.069	5.746	5.793
Infoweek 500$_{it}$	15,525	0.039	0.192	0.000	0.000	0.000
CIO$_{it}$	19,828	0.677	0.468	0.000	1.000	1.000
Product Market Competition$_{it}$	28,655	0.601	0.490	0.000	1.000	1.000
Industry Downturn$_{it}$	26,251	0.548	0.498	0.000	1.000	1.000
High#SDKs$_{it}$	28,655	0.105	0.306	0.000	0.000	0.000
Location$_{it}$	28,655	0.106	0.308	0.000	0.000	0.000
Contact$_{it}$	28,655	0.076	0.265	0.000	0.000	0.000
Personal$_{it}$	28,655	0.117	0.321	0.000	0.000	0.000

$Financial_{it}$	28,655	0.042	0.200	0.000	0.000	0.000
$Search_{it}$	28,655	0.032	0.177	0.000	0.000	0.000
$App\ Launch[0]_{it}$	28,655	0.017	0.128	0.000	0.000	0.000
$App\ Launch[1]_{it}$	28,655	0.017	0.129	0.000	0.000	0.000
$App\ Launch[2+]_{it}$	28,655	0.113	0.317	0.000	0.000	0.000

Panel B: Frequency and Mean of *App Launch* by Fiscal Year

Fiscal Year	**#Obs.**	**%**	**Mean of *App Launch***
2006	2,053	7.16	0.000
2007	2,169	7.57	0.000
2008	2,081	7.26	0.002
2009	2,024	7.06	0.015
2010	1,932	6.74	0.032
2011	1,854	6.47	0.073
2012	1,772	6.18	0.115
2013	1,747	6.10	0.141
2014	1,792	6.25	0.174
2015	1,786	6.23	0.205
2016	1,687	5.89	0.231
2017	1,555	5.43	0.265
2018	1,495	5.22	0.290
2019	1,605	5.60	0.314
2020	1,629	5.68	0.324
2021	1,474	5.14	0.328
Total	28,655	100.00	0.143

Panel C: Frequency and Mean of *App Launch* by Industry

GIC 2-Digit	GIC 6-Digit	GIC Industry Name	#Obs.	%	Mean of *App Launch*
Industrials	201050	Industrial Conglomerates	121	0.42	0.132
	202010	Commercial Services & Supplies	1,611	5.62	0.038
	202020	Professional Services	969	3.38	0.104
	203010	Air Freight & Logistics	255	0.89	0.118
	203020	Airlines	420	1.47	0.314
	203040	Road & Rail	621	2.17	0.116
Customer - Discretionary	251020	Automobiles	274	0.96	0.339
	252010	Household Durables	1,102	3.85	0.082
	252020	Leisure Products	350	1.22	0.091
	252030	Textiles, Apparel & Luxury Goods	936	3.27	0.126
	253010	Hotels, Restaurants & Leisure	2,099	7.33	0.192
	253020	Diversified Customer Services	681	2.38	0.137
	254010	Media	509	1.78	0.057
	255010	Distributors	161	0.56	0.068
	255020	Internet & Direct Marketing Retail	583	2.03	0.338
	255030	Multiline Retail	253	0.88	0.213
	255040	Specialty Retail	1,821	6.35	0.201
Customer - Staples	301010	Food & Staples Retailing	673	2.35	0.186
	302010	Beverages	629	2.20	0.076
	302030	Tobacco	130	0.45	0.054
	303010	Household Products	216	0.75	0.111
	303020	Personal Products	650	2.27	0.095
Health Care	351020	Health Care Providers & Services	1,584	5.53	0.037
	351030	Health Care Technology	410	1.43	0.080
Information Technology	451010	Internet Software & Services	550	1.92	0.069
	451020	IT Services	1,657	5.78	0.124
	451030	Software	3,332	11.63	0.139
	452020	Tech. Hardware, Storage & Peripherals	725	2.53	0.148
Communication Services	501010	Diversified Telecom. Services	1,203	4.20	0.102
	501020	Wireless Telecommunication Services	396	1.38	0.301
	502010	Media	1,120	3.91	0.224
	502020	Entertainment	664	2.32	0.312
	502030	Interactive Media & Services	560	1.95	0.366
Utilities	551010	Electric Utilities	729	2.54	0.103
	551030	Multi-Utilities	394	1.37	0.104
	551040	Water Utilities	267	0.93	0.041
	Total		28,655	100.00	0.143

Table 2
Correlation Table

This table presents Pearson correlations among variables used in the primary regression analyses. Variables are defined in Appendix A.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
(1) $\lvert Abnormal\ Investment_{it} \rvert$	1.00									
(2) $Inventory\ Turnover_{it}$	0.04***	1.00								
(3) $App\ Launch_{it}$	-0.01	0.05***	1.00							
(4) $Assets_{it}$	-0.15***	0.07***	0.29***	1.00						
(5) Age_{it}	-0.13***	-0.09***	0.09***	0.36***	1.00					
(6) $Leverage_{it}$	-0.01**	0.13***	0.06***	0.01**	0.03***	1.00				
(7) $\#Analysts_{it}$	-0.03***	0.02**	0.29***	0.55***	0.18***	-0.03***	1.00			
(8) $\%Institutional_{it}$	-0.06***	-0.06***	0.15***	0.33***	0.26***	-0.06***	0.54***	1.00		
(9) $Revenue\ Volatility_{it}$	0.09***	0.02**	-0.08***	-0.41***	-0.23***	0.14***	-0.18***	-0.15***	1.00	
(10) $Asset\ Turnover_{it}$	-0.04***	-0.07***	-0.06***	-0.27***	0.03***	0.10***	-0.06***	0.06***	0.40***	1.00

Table 3
Investment Efficiency Following the Launch of a Mobile App

This table reports results from regression analyses of abnormal investment. Column (1) reports the OLS regression results for the full sample of 28,655 firm-year observations from 2006 to 2021. Columns (2) and (3) report OLS regression results after partitioning the sample based on whether the investment residuals are non-negative or negative. The final two columns present results from a stacked DiD analysis, by constructing a cohort of treatment firms of the same app launch year paired with control firms that have never adopted apps or that adopt apps in the later period (Column (4)), or with control firms that have never adopted apps (Column (5)). Regressions include controls and fixed effects as indicated. *t*-statistics in parentheses are based on standard errors clustered by firm. ***, **, and * denote significance level at the 1%, 5%, and 10% levels (two-tailed). All variables are defined in Appendix A.

	OLS	**OLS**	**OLS**	**Stacked**	**Stacked**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Dependent Variable =	$\lvert$***Abnormal Investment***$_{it}\rvert$				
Sample =	**All**	**> 0**	**< 0**	**All**	**All**
App Launch$_{it}$	**-0.046***	**0.037**	**-0.082****	**-0.057*****	**-0.045*****
	(-1.86)	**(0.98)**	**(-2.36)**	**(-2.66)**	**(-2.87)**
Assets$_{it}$	0.005	-0.021	0.010	0.012**	-0.033***
	(0.23)	(-0.76)	(0.39)	(2.01)	(-30.95)
Age$_{it}$	0.010	-0.141*	0.168**	-0.001	-0.059***
	(0.16)	(-1.62)	(2.01)	(-0.07)	(-20.61)
Leverage$_{it}$	-0.090**	-0.040	-0.068	-0.084***	-0.023***
	(-2.02)	(-0.43)	(-1.27)	(-6.35)	(-3.48)
#Analysts$_{it}$	0.002	-0.007**	0.009***	0.003***	0.003***
	(0.78)	(-1.98)	(2.85)	(3.74)	(12.14)
%Institutional$_{it}$	0.007	0.017	0.003	0.009	-0.023***
	(0.17)	(0.38)	(0.05)	(0.76)	(-5.18)
Revenue Volatility$_{it}$	0.091*	0.165**	0.004	0.080***	0.239***
	(1.74)	(2.13)	(0.05)	(5.45)	(22.14)
Asset Turnover$_{it}$	-0.028	-0.091***	0.006	-0.031***	-0.049***
	(-1.19)	(-2.54)	(0.18)	(-4.51)	(-17.22)
Firm & year FE	Yes	Yes	Yes	No	No
Cohort-firm & cohort-year FE	No	No	No	Yes	No
Cohort-industry & cohort-year FE	No	No	No	No	Yes
Observations	28,655	11,233	16,300	303,163	299,691
Adjusted R^2	14.0%	23.5%	14.4%	13.7%	10.8%

Table 4
Inventory Management Following the Launch of a Mobile App

This table reports results from regression analyses of inventory turnover. Column (1) reports the OLS regression results for the full sample of 20,689 firm-year observations from 2006 to 2021. In Columns (2)-(4), we repeat the analysis by using raw material, work-in-process, and finished goods inventory to calculate inventory turnover, respectively. The final two columns present results from a stacked DiD analysis, by constructing a cohort of treatment firms of the same app launch year paired with control firms that have never adopted apps or that adopt apps in the later period (Column (5)), or with control firms that have never adopted apps (Column (6)). Regressions include controls and fixed effects as indicated. *t*-statistics in parentheses are based on standard errors clustered by firm. ***, **, and * denote significance level at the 1%, 5%, and 10% levels (two-tailed). Variables are defined in Appendix A.

	OLS	**OLS**	**OLS**	**OLS**	**Stacked**	**Stacked**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable =	***Inventory Turnover$_{it}$***	***Inventory Turnover_RM$_{it}$***	***Inventory Turnover_WIP$_{it}$***	***Inventory Turnover_FG$_{it}$***	***Inventory Turnover$_{it}$***	***Inventory Turnover$_{it}$***
App Launch$_{it}$	**0.043****	**0.198*****	**-0.020**	**0.113****	**0.046****	**0.153*****
	(1.98)	**(2.87)**	**(-0.19)**	**(2.02)**	**(2.34)**	**(3.60)**
Assets$_{it}$	-0.052**	-0.081	-0.000	-0.058	-0.057***	-0.068***
	(-1.93)	(-1.35)	(-0.00)	(-1.29)	(-7.30)	(-9.36)
Age$_{it}$	0.064	0.032	-0.718***	-0.071	0.049***	-0.103***
	(1.05)	(0.17)	(-3.66)	(-0.49)	(2.48)	(-11.78)
Gross Margin$_{it}$	-0.141***	-0.027	-0.028	-0.181***	-0.143***	-0.202***
	(-3.66)	(-0.41)	(-0.65)	(-2.72)	(-12.95)	(-15.84)
Capital Intensity$_{it}$	0.021	0.081	0.249***	0.090**	0.022***	0.102***
	(0.89)	(1.38)	(4.19)	(2.24)	(3.05)	(15.28)
Revenue Volatility$_{it}$	0.083**	-0.014	0.132	0.051	0.130***	0.764***
	(2.06)	(-0.16)	(1.16)	(0.62)	(10.38)	(31.44)
Revenue Growth$_{it}$	0.179***	0.222***	0.056	0.270***	0.172***	0.140***
	(9.71)	(5.70)	(1.29)	(7.32)	(32.53)	(18.55)
Segments$_{it}$	0.002	-0.009	0.028	0.009	0.005***	-0.018***
	(0.32)	(-0.64)	(1.38)	(0.79)	(2.77)	(-7.46)
Foreign Sales$_{it}$	-0.030	-0.086*	-0.031	-0.071	-0.030***	-0.082***
	(-1.32)	(-1.65)	(-0.38)	(-1.50)	(-4.10)	(-6.64)
ROA$_{it}$	0.112***	0.101	0.145**	0.132***	0.095***	0.232***
	(3.01)	(1.46)	(1.95)	(2.56)	(9.09)	(18.92)
Big-4 Auditor$_{it}$	0.028	-0.005	0.097	-0.019	0.042***	0.049***
	(0.83)	(-0.06)	(0.95)	(-0.27)	(4.18)	(3.36)
Loss$_{it}$	-0.024**	-0.013	-0.010	-0.086***	-0.026***	-0.023***
	(-2.11)	(-0.45)	(-0.28)	(-3.01)	(-7.22)	(-2.58)

Firm & year FE	Yes	Yes	Yes	Yes	No	No
Cohort-firm & Cohort-year FE	No	No	No	No	Yes	No
Cohort-industry & Cohort-year FE	No	No	No	No	No	Yes
Observations	20,689	9,682	9,682	9,682	215,026	212.204
Adjusted R^2	91.5%	84.4%	83.8%	82.3%	90.7%	44.8%

Table 5
Investment Efficiency and Inventory Management Following Privacy Initiatives

This table reports results from OLS regressions of abnormal investment and inventory turnover around privacy initiatives. Columns (1)-(2), (3)-(4), and (5)-(6) examine the General Data Protection Regulation (GDPR), California Customer Privacy Act (CCPA), and Apple Privacy Nutrition Label (PNL) requirement settings, respectively. We restrict the sample to the period after 2015 in Columns (1)-(2) and after 2018 in Column (3)-(6), and firms that have not released a mobile app by the start of the sample period are excluded. Odd (even) columns report estimation results for investment efficiency (inventory turnover). Regressions include controls and fixed effects as indicated. *t*-statistics in parentheses are based on standard errors clustered by firm. ***, **, and * denote significance level at the 1%, 5%, and 10% levels (two-tailed). All variables are defined in Appendix A.

Regulation =	**GDPR**		**CCPA**		**Apple's PNL**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Dependent Variable =	$\lvert$***Abnormal Investment***$_{it}\rvert$	***Inventory Turnover***$_{it}$	$\lvert$***Abnormal Investment***$_{it}\rvert$	***Inventory Turnover***$_{it}$	$\lvert$***Abnormal Investment***$_{it}\rvert$	***Inventory Turnover***$_{it}$
Affected$_i$×***Post***$_t$	**0.146****	**-0.116****	**0.576***	**-0.109***	**0.194*****	**-0.087****
	(2.33)	**(-2.45)**	**(1.84)**	**(-1.91)**	**(2.83)**	**(-1.99)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,388	1,755	1,792	1,246	1,792	1,246
Adjusted R^2	22.6%	95.8%	28.8%	96.3%	29.0%	96.8%

Table 6
Why Do Mobile Apps Help? Better Information versus More Stable Fundamentals?

This table reports results from OLS regressions of revenue volatility, revenue persistence, and earnings and revenue forecast errors. Column (1) reports regression results of revenue volatility on mobile app launch. Columns (2) reports regression results of next year revenue on mobile app launch, current sales revenue, and their interaction. Columns (3) and (4) report regression results of management earnings and revenue forecast errors on mobile app launch. All regressions include controls and fixed effects as indicated. *t*-statistics in parentheses are based on standard errors clustered by firm. ***, **, and * denote significance level at the 1%, 5%, and 10% levels (two-tailed). Variables are defined in Appendix A.

	(1)	(2)	(3)	(4)
Dependent Variable =	***Revenue Volatility*$_{it+1}$	***Revenue*$_{it+1}$	|***Earnings Forecast Error***$_{it}$|	|***Revenue Forecast Error***$_{it}$|
***App Launch*$_{it}$**	**0.007**	**0.009**	**-0.011****	**-0.014***
	(1.52)	**(0.85)**	**(-2.32)**	**(-1.68)**
***Revenue*$_{it}$**		**0.076*****		
		(3.81)		
***Revenue*$_{it}$ × *App Launch*$_{it}$**		**-0.045**		
		(-0.62)		
Assets$_{it}$	-0.019***	-0.168***	0.002	-0.017**
	(-5.11)	(-13.52)	(0.36)	(-2.32)
Age$_{it}$	-0.052***	-0.118***	-0.009	-0.025
	(-5.11)	(-3.93)	(-0.58)	(-0.92)
Leverage$_{it}$	-0.005	0.016	0.042***	0.106***
	(-0.65)	(0.66)	(3.26)	(5.16)
#Analysts$_{it}$	0.000	0.001	-0.000	-0.003***
	(0.33)	(0.84)	(-0.70)	(-4.29)
%Institutional$_{it}$	0.006	0.008	-0.016*	-0.001
	(0.86)	(0.50)	(-1.71)	(-0.03)
Revenue Volatility$_{it}$	-0.094***	-0.029	-0.004	0.008
	(-8.57)	(-1.28)	(-0.41)	(0.41)
Asset Turnover$_{it}$	0.059***	-0.357***	0.004	-0.036***
	(8.81)	(-20.54)	(0.62)	(-2.92)
Earnings Forecast Horizon$_{ti}$			0.004***	
			(5.24)	
Revenue Forecast Horizon$_{ti}$				0.016***
				(10.18)
Firm & year fixed effects	Yes	Yes	Yes	Yes
Observations	26,262	28,417	5,552	5,552
Adjusted R^2	57.5%	25.1%	71.2%	30.3%

Table 7
Under What Conditions Do Mobile Apps Help?

This table reports results from OLS regressions of abnormal investment and inventory turnover across various sub-samples. Panel A presents results based on whether the firm has high or low internal information system quality. Columns (1)-(4) report results based on whether the firm belongs to the top Information Week 500 ranking. The sample is limited to the period before 2013 due to data availability. Columns (5)-(8) report results based on whether the firm the firm has a Chief Information Officer or Chief Technology Officer on the board. Panel B presents results based on different product market and economic conditions. Columns (1)-(4) report results based on whether the firm faces high product market competition. Columns (5)-(8) reports results based on whether the firm experiences an industry downturn. Regressions include controls and fixed effects as indicated. *t*-statistics in parentheses are based on standard errors clustered by firm. ***, **, and * denote significance level at the 1%, 5%, and 10% levels (two-tailed). All variables are defined in Appendix A.

Panel A: Internal Information System Quality

	Information Week Top 500				**Top Chief Information Officer (CIO)**			
	Yes	No	Yes	No	Yes	No	Yes	No
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Dependent Variable =	$\|$***Abnormal Investment***$_{it}\|$		***Inventory Turnover***$_{it}$		$\|$***Abnormal Investment***$_{it}\|$		***Inventory Turnover***$_{it}$	
App Launch$_{it}$	**-0.161****	**0.077**	**0.124****	**0.045**	**-0.054***	**-0.035**	**0.047***	**0.026**
	(-2.02)	**(1.59)**	**(2.06)**	**(1.39)**	**(-1.69)**	**(-0.91)**	**(1.72)**	**(0.74)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm & year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	521	14,848	414	10,991	13,310	15,025	8,817	11,613
Adjusted R^2	8.2%	7.3%	98.3%	93.7%	17.8%	15.9%	93.2%	91.1%
	Comparison of *App Launch*$_{it}$							
	Between Cols (1) and (2)		Between Cols (3) and (4)		Between Cols (5) and (6)		Between Cols (7) and (8)	
p-value	0.054		<0.001		0.392		0.032	

Panel B: Product Market and Economic Conditions

	Product Market Competition				**Industry Downturn**			
	High	Low	High	Low	Yes	No	Yes	No
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Dependent Variable =	$\|$***Abnormal Investment***$_{it}$$\|$		***Inventory Turnover***$_{it}$		$\|$***Abnormal Investment***$_{it}$$|$		***Inventory Turnover***$_{it}$	
App Launch$_{it}$	**-0.125****	**-0.006**	**0.077****	**0.016**	**-0.046***	**0.011**	**0.035***	**0.024**
	(-2.37)	**(-0.22)**	**(2.32)**	**(0.56)**	**(-1.73)**	**(0.27)**	**(1.83)**	**(0.82)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
Observations	11,379	17,185	8,618	12,015	13,965	11,421	11,756	8,291
Adjusted R^2	20.0%	9.2%	90.7%	92.4%	10.2%	12.0%	92.7%	90.6%
	Comparison of *App Launch*$_{it}$							
	Between Cols (1) and (2)		Between Cols (3) and (4)		Between Cols (5) and (6)		Between Cols (7) and (8)	
p-value	0.004		0.032		0.068		0.008	

Table 8
How Do Mobile Apps Help?

This table reports results from OLS regressions of abnormal investment and inventory turnover based on characteristics of the mobile app. Panel A reports the results after including the indicator variable for firms having apps with high number of software development kits ($High\#SDK_{it}$). Panel B reports the results by including app launch indicators by the content of collected data ($Location_{it}$, $Contact_{it}$, $Personal_{it}$, $Financial_{it}$, $Search_{it}$). Regressions include controls and fixed effects as indicated. *t*-statistics in parentheses are based on standard errors clustered by firm. ***, **, and * denote significance level at the 1%, 5%, and 10% levels (two-tailed). All variables are defined in Appendix A.

Panel A: Number of Software Development Kits

	(1)	(2)
Dependent Variable =	$\lvert Abnormal\ Investment_{it}\rvert$	$Inventory\ Turnover_{it}$
$App\ Launch_{it}$	**0.022**	**-0.014**
	(0.51)	**(-0.37)**
$App\ Launch_{it} \times High\#SDK_{it}$	**-0.096****	**0.079***
	(-2.01)	**(1.90)**
Controls	Yes	Yes
Firm & year fixed effects	Yes	Yes
Observations	28,655	20,689
Adjusted R^2	14.0%	91.5%

Panel B: Individual Mobile App Features

	(1)	(2)
Dependent Variable =	$\lvert Abnormal\ Investment_{it}\rvert$	$Inventory\ Turnover_{it}$
$Location_{it}$	**-0.156****	**-0.038**
	(-2.30)	**(-0.66)**
$Contact_{it}$	**0.076**	**0.010**
	(1.32)	**(0.19)**
$Personal_{it}$	**0.063**	**0.013**
	(1.02)	**(0.26)**
$Financial_{it}$	**-0.106****	**0.106****
	(-2.36)	**(1.93)**
$Search_{it}$	**0.085**	**0.000**
	(1.42)	**(0.00)**
Controls	Yes	Yes
Firm & year fixed effects	Yes	Yes
Observations	28,655	20,689
Adjusted R^2	14.0%	90.1%

Table 9
How Quickly Do Mobile Apps Help?

This table reports results from OLS regressions of abnormal investment and inventory turnover, allowing for different effects in event time. *App Launch[0]*$_{it}$ is an indicator variable equal to one if app was released in the current year, *App Launch[1]*$_{it}$ is an indicator variable equal to one if app was released in the previous year, and *App Launch[2+]*$_{it}$ is an indicator variable equal to one if app was released two or more years prior. Regressions include controls and fixed effects as indicated. *t*-statistics in parentheses are based on standard errors clustered by firm. ***, **, and * denote significance level at the 1%, 5%, and 10% levels (two-tailed). All variables are defined in Appendix A.

	(1)	**(2)**
Dependent Variable =	$\lvert$***Abnormal Investment***$_{it}\rvert$	***Inventory Turnover***$_{it}$
App Launch[0]$_{it}$	-0.001	0.030*
	(-0.02)	(1.85)
App Launch[1]$_{it}$	0.015	0.028*
	(0.33)	(1.68)
App Launch[2+]$_{it}$	-0.075***	0.047***
	(-3.33)	(3.63)
Controls	Yes	Yes
Firm & year fixed effects	Yes	Yes
Observations	28,655	20,689
Adjusted R^2	14.0%	91.5%