Acquisition of Customer Information and Corporate Decision Making

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ABSTRACT

This study examines the value of customer data collected through mobile apps for firms' investing and operating decisions. We find that following the introduction of a mobile app, management earnings and revenue guidance is more accurate, and firms exhibit less underinvestment in capital assets and less overinvestment in inventory, particularly for firms with effective internal information systems. 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 operating decisions. However, we find that privacy regulations intended to protect customers restrict firms' ability to access these efficiency gains.

JEL Classifications: G31, M41, D83

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1. 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). We examine whether technologies that allow firms to collect customer information for marketing purposes also facilitate investing and operating decisions. Further, we investigate whether privacy regulations intended to protect customers restrict firms' ability to access these efficiency gains, an unintended consequence that could potentially harm customers, for example, by way of higher prices.

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 100 billion hours on mobile shopping apps in 2021, browsing new products, making and tracking purchases, and communicating with service agents (Reed 2022). Revenue generated through mobile apps reached $3.6 trillion worldwide in 2021, about four times the revenue generated just five years earlier. In the U.S., 7.3% of total retail sales originate from mobile apps (Curry 2022). Even customers who shop in-store frequently use mobile apps, for example to browse products or identify discounts. More than half of customers have used a retailer's mobile app while shopping in-store (Mulligan 2019).

With more and more customers using mobile shopping apps, firms have access to increasing amounts of data that can provide timely and valuable customer insights. Commonly tracked metrics include the number of daily users; demographics such as age, gender, and location; products viewed and conversion rates; new and repeat purchases; user retention rates; revenue per user; time spent on the app; ratings and reviews; etc. Through mobile apps, firms may also have access to a customer's GPS location and data from third-party apps linked through the customer's phone identifier. Much of this information would be difficult to collect and analyze outside of mobile apps. As such, the information obtained through mobile apps can aid managers not only to increase sales through enhanced marketing efforts but also to forecast future sales, which is a basis for important investing and operating decisions. Thus, we expect mobile apps to allow firms to improve not only the effectiveness of marketing programs, as documented in prior literature (e.g., Peng, Chen, and Wen 2014, Kim and Yu 2016), but also to make superior business decisions. For example, by leveraging customer information, firms can make more efficient capital investment decisions, i.e., they will exhibit less capital misallocation 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.

We investigate whether mobile apps aid managerial decision making using data on the release of firms' mobile apps and features that enable the collection of customer data. We start by studying the relation between app adoption and both investment and production decisions. We document that, consistent with our hypotheses, firms exhibit higher investment efficiency, as manifested in less underinvestment in capital assets, and higher inventory management efficiency, as manifested in less overinvestment in inventory, following the release of a mobile shopping app. We then extend our investigations to settings where firms' ability to collect customer information declined because of initiatives intended to protect customer privacy. Studying these initiatives is interesting in its own right because it can inform regulators about possible unintended consequences of their actions. At the same time, these settings have the added benefit of helping us address endogeneity concerns. Because firms choose to release apps, firms releasing apps differ along unobservable dimensions from firms that do not release apps, and these differences may explain our findings. Studying privacy actions help mitigate these concerns because these initiatives (i) are exogenous to any one firm and (ii) affect firms that use mobile apps and meet certain conditions but do not affect firms without mobile apps, thus providing a natural set of treatment and control firms.

We focus our attention toward three different initiatives. 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 app users' 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 app user. 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 mobile apps used by 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 will have less access to customer information from mobile apps and thus less information about customer demand following the implementation of these privacy actions. Consequently, we expect and document that more affected firms experience declines in the quality of their investing and operating decisions.

Overall, our main 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 operating decisions. However, these results may also be consistent with mobile apps resulting in more stable consumer demand because they increase customer engagement and retention. 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 earnings and revenue forecasts. 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 indicate that firms with mobile apps benefit from superior information, but not necessarily more stable demand for their products, which is consistent with our story.

Next, we attempt to identify conditions under which the information benefits of mobile apps are larger. We document two patterns in the data. First, the information benefits of mobile apps appear to concentrate among firms with superior internal information system quality, consistent with the notion that taking advantage of the data supplied by mobile apps may require firms to have an adequate technological infrastructure in place. Second, the information benefits of mobile apps appear to concentrate on situations where the benefits of superior information are larger, such as when product market competition is high or during industry downturns.

Finally, we investigate which app features seem to be most beneficial for managers' investment and production decisions. We find that the positive association between mobile apps and investing and operating efficiency is larger when the apps have features that allow for the collection of a greater quantity and quality of customer information. We also document that the collection of customers' location and financial information is associated with more efficient investment decisions, while the collection of customers' financial information is associated with more efficient operating decisions. We do not find significant associations between the efficiency of these decisions and the collection of other personal data, customers' contacts, or customers' search histories.

Our study makes several contributions to the academic literature and informs regulators. First, our findings highlight the unintended consequences of customer privacy regulation. Recently, more and more state regulators in the U.S. are implementing data privacy laws to protect customers. Starting with California in 2020, Utah, Connecticut, Virginia, and Colorado passed customer privacy laws in 2022 (Jaworski and Schmeltzer 2022). 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 privacy regulations has focused on how these regulations affect 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, Presidente 2022). Ours is the first study we are aware of that considers the value of customer information gathered through mobile apps for investing and operating decisions, as well as the negative consequences of privacy regulations on these decisions. Our findings indicate that these regulations, while protecting customer privacy, reduce the amount and quality of information available to firms when making investing and operating 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. At the same time, we would like to 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 need to weigh against the benefits when making policy decisions.

Second, 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 2022). We contribute to this literature by documenting that mobile apps allow managers to systematically gather the information that is relevant to their decisions but would be otherwise difficult to collect. In this regard, our paper also speaks to the developing literature exploring potential uses of big data. Much of this literature has focused on the use of big data by investors. 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 2022, Katona, Painter, and Patatoukas 2022). Our study investigates the role of big data in firms' internal information environment and in investing and operating decisions. This complements recent work by Charoenwong, Kowaleski, Kwan, and Sutherland (2022), who document that technological investments allow firms to reduce customer complaints and employee misconduct; Labro, Lang, and Omartian (2022), 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.

Lastly, we contribute to the literature on mobile apps. Marketing and information systems literatures have examined the value of mobile app investment. For example, Yuan, Chen, and Sia (2021) investigate the market valuation of mobile apps, and Einav, Levin, Popov, and Sundaresan (2014) study the effect of mobile apps on revenues. We complement and extend these literatures by showing that mobile apps improve firm efficiency by alleviating uncertainty about a firm's operating environment. We also highlight the potential role of mobile apps in providing real-time information about customer demand.

2. Background and Hypothesis Development

2.1 Institutional Background

Prior to the introduction of e-commerce and eventually mobile apps, retailers had relatively few means to acquire detailed information about their customers.[1] The introduction of mobile shopping apps created new opportunities for firms to collect 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 million apps and 3.5 million apps, respectively, serving users worldwide. As such, 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 2021, about four times the revenue generated just five years earlier (Reed 2022). In the U.S., 7.3% of total retail sales originate from mobile apps (Curry 2022). Even customers who shop in-store frequently use mobile apps to browse products or identify discounts. For example, more than half of customers have used a retailer's mobile app while shopping in-store (Mulligan 2019). As customer

[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.

engagement with mobile apps increases, the quality and quantity of customer data available to firms increases 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. This information can include the device identifier, GPS location, personal information (e.g., contacts, call log, and calendar), 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.

2.2 Main Predictions

2.2.1 Corporate Decision Making

The customer information collected from mobile apps can help managers not only to increase their sales but also to forecast future sales more accurately. As such, we expect that apps can help managers make superior investing and operational decisions.

One important input into capital investment decisions is future demand for the firm's products and services. For example, if expected demand is high, a manager may increase capital investment to increase production capacity for existing products, expand into new territories, or

[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.

introduce new products. However, in the presence of uncertainty about future demand, managers (i) invest less and (ii) adopt a wait-and-see strategy in which they delay their (irreversible) investment decisions, which reduces 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), then the adoption of mobile apps can help managers reduce uncertainty about future demand and facilitate their investment decision making.

H1: Investment efficiency increases following the release of a mobile app.

The presence of uncertainty influences not only managers' investment decisions, but also their operating decisions. In the presence of higher uncertainty about future demand, managers increase their inventory holdings, thus trading off the holding cost of inventory with a reduction in the likelihood of experiencing costly stock-outs in case of unexpected demand (Rubin 1980, Bo 2001, Caglayan, Maioli, and Mateut 2012). If the data collected by mobile apps allows managers to more accurately forecast demand, then inventory levels can be managed more efficiently.

H2: Inventory efficiency increases following the release of a mobile app.

Given the possible benefits from releasing mobile apps, one may question why all firms do not release apps. There are a few reasons why we expect to see variation in the use of mobile apps among our sample firms. First, mobile apps are likely to be released for marketing purposes, with the goal of increasing customer engagement and ultimately purchases. The collection and availability of customer data to inform investing and operating decisions is likely to be a secondary benefit of having a mobile app, but not the primary motivation for releasing one. For some firms, the business model or customer base is not suitable for the use of a mobile app (e.g., firms that have a concentrated customer base or do not sell to consumers, e.g., defense contractors or mining companies, or firms with restrictions on the marketing of their products, e.g., cigarette companies).

To the extent that collecting customer data is a factor in the decision to release a mobile app, the costs and benefits to collecting, processing, sharing, and using this data are likely to vary across firms. In terms of costs, Charoenwong et al. (2022) discuss how adopting new technologies may require firms to have adequate information systems in place. When firms' information systems are inadequate, they may be required to make substantial investments in information systems to fully realize the benefits of customer information collected through mobile apps. For these firms, the costs involved may not be justified by the potential benefits. The benefits of mobile apps may also vary with the quality of internal information systems. Further, the benefits 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 (Granadier 2002) and during economic downturns (Kacperczyk, Nieuwerburgh, and Veldkamp 2016, Loh and Stulz 2018).

2.2.2 Privacy Actions

As the amount of customer data collected has dramatically increased in recent years, customer privacy has become an important issue for customer advocates and politicians. This has led to actions taken by regulators and app stores to protect customer privacy. Recently in the U.S., this has been evident in the state regulators that are implementing data privacy laws to protect customers. For example, following the example of California, which passed customer privacy laws in 2020, Connecticut, Virginia, and Colorado passed similar laws in 2022 (Jaworski and Schmeltzer 2022). 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 through mobile apps, as intended by the privacy actions discussed above and other similar initiatives, their investment and operating decisions may be less efficient. Accordingly, we make the following hypothesis:

H3: Investment and inventory efficiency decrease following privacy actions.

3. Sample and Variables

3.1 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. 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 the apps of its subsidiary, Whole Foods Market.

We restrict our sample to apps operated in the U.S. with English as the primary language. Our sample begins in 2006, which is two years before the first app release,[3] 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 GIC (Global Industry Classification) six-digit industries with at least 10% of firms that have launched mobile shopping

[3] Our inferences are qualitatively similar when using a sample period that begins in 2008.

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 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.

3.2 Measurement of Key Variables

The three 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.

We measure investment efficiency using abnormal investment as in McNichols and Stubben (2008).[4] We calculate abnormal investment as the absolute value of the residuals from the following regression model, estimated by industry and year:

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

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

[4] As an alternative approach, we measure investment efficiency using the sensitivity of investment to investment opportunities. Our findings with this approach, which are reported in Table A3 of the online appendix, are consistent with those based on our main approach.

investment. CF_t is measured as 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*. $Investment_{it-1}$ is capital expenditures, scaled by beginning-of-year net PP&E. We estimate equation (1) by GIC six-digit-year group and require each group to include at least 10 observations. We use the absolute value of residuals, namely the portion of investments unexplained by firms' growth opportunities, to measure investment inefficiency ($|Abnormal\ Investment_{it}|$). Lower values of $|Abnormal\ Investment_{it}|$ indicate higher investment efficiency.

Finally, we measure the efficiency of inventory management using inventory turnover ($Inventory\ Turnover_{it}$). We calculate this variable as the natural logarithm of cost of goods sold scaled by the average inventory during the fiscal year, where the logarithmic transformation is necessary because the resulting variable is highly skewed to the right.

3.3 Descriptive Statistics

Table 1, Panel A, presents descriptive statistics for our sample. All continuous variables are winsorized at the 2nd and 98th percentiles. The mean of *App Launch* indicates that an app has been launched for 14% of firm-year observations. Panel B reveals that the mean of *App Launch* increases from 0% to 33% throughout the sample period. Panel C presents the mean of *App Launch* by industry. Substantial variation in mobile app adoption rates is evident both within and across two-digit industries. Among six-digit industries, Interactive Media & Services (36.6%), Automobiles (33.9%), Internet & Direct Marketing Retail (33.8%), Airlines (31.4%), and Entertainment (31.2%) industries have the highest means of *App Launch*. Health Care Providers & Services (3.7%), Commercial Services & Supplies (3.8%), Water Utilities (4.1%), and Tobacco (5.4%) have the lowest means of *App Launch*.

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), thus lending preliminary support to our hypotheses.

4. Research Design and Empirical Results

4.1 Investment Efficiency Following the Launch of a Mobile App

We test our prediction that investment efficiency improves after the release of a mobile app 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 in Section 3.2. We follow the prior literature (i.e., Chen, Hope, Li, and Wang 2011, Cohen and Li 2020) by including the following 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 over the previous twelve quarters, scaled by current quarterly revenue ($Revenue\ Volatility_{it}$); and revenue scaled by assets ($Asset\ Turnover_{it}$). We include firm fixed effects as a control for time-invariant firm characteristics and year fixed effects as a control for variation in abnormal investment over time. Standard errors are clustered by firm.

Under H1, we expect that investment efficiency improves following the initial release of a mobile app. Hence, we expect to observe a negative estimated β_1 coefficient. Table 4, which reports our coefficient estimates for Equation (2), lends empirical support to our prediction. The negative and statistically significant coefficient on $App\ Launch_{it}$ (coeff. = -0.046; t-stat = -1.88) indicates the improvement in investment efficiency following the release of a mobile app. In economic terms, the initial release of a mobile app is associated with a decrease in abnormal investments of 5% of net PP&E, or 5% of the standard deviation of $|Abnormal\ Investment_{it}|$.[5]

We next explore whether this improvement in investment efficiency stems from 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 overinvesting and underinvesting firms, and report estimated coefficients in Columns (2) and (3), respectively. We document that the launch of a mobile app is associated with a reduction in underinvestment but has no association with overinvestment, as indicated by negative and significant coefficient in Column (3) (coeff. = -0.082; t-stat = -2.37) and insignificant coefficient in Column (2) (coeff. = 0.036; t-stat = 0.96). 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.

Overall, the evidence presented in Table 4 is consistent with mobile apps leading to improved investment efficiency, primarily by reducing underinvestment.

4.2 Inventory Management Following the Launch of a Mobile App

We next test our second hypothesis the quality of managers' operating decisions improves following the release of a mobile app, specifically their inventory management. We estimate the following OLS regression:

$$\begin{aligned} Inventory\ Turnover_{it} = \beta_0 + \beta_1 App\ Launch_{it} + Controls \\ + Firm\ fixed\ effects + Year\ fixed\ effects + \varepsilon_{it}, \end{aligned} \tag{3}$$

[5] Our inferences are unchanged when we include additional controls for the information environment (i.e., unqualified audit opinion and Big N auditors).

where *Inventory Turnover*$_{it}$ and *App Launch*$_{it}$, are defined as in Section 3.2, and the controls are the same as used in Equation (2).

Under H2, we expect that inventory management efficiency improves following the initial release of a mobile app. Hence, we expect to observe a positive estimated β_1 coefficient. Table 4, which presents the estimation results of Equation (3), provides support to our hypothesis. In Column (1), β_1 is significant and positive (coeff. = 0.039; t-stat = 1.83), suggesting that inventory turnover improves by 4% following the launch of a mobile app.[6] For the subsample of firms that report a breakdown of raw materials, work-in-process, and finished goods, we find that the increase in inventory turnover following the introduction of mobile apps is evident for raw materials (coeff. = 0.167; t-stat = 2.41) and finished goods (coeff. = 0.113; t-stat = 2.03), but not for work-in-process (coeff. = -0.011; t-stat = -0.11).

Taken together, this evidence is consistent with mobile apps leading to improved inventory management efficiency, especially for raw materials and finished goods.

4.3 The Effect Privacy Regulations and Policies

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 multiple "privacy actions", namely actions by regulators and app stores to protect customer privacy. These actions have combined to limit the amount and quality of customer information available to firms. As these limit the amount of personal customer data that companies can collect, we expect that the value of mobile apps for investing and operating decisions will decrease following their introduction. We focus on three such privacy actions and their effects on

[6] These findings become stronger (coeff.: 0.051; t-stat: 2.39) 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).

the efficiency of firms' investment and inventory management: 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 use a difference-in-differences approach to study the change in investment and inventory efficiency in the window around each privacy action. 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 affected or not affected by the action. We estimate the following regression specification on three separate samples:[7]

$$\begin{aligned} Y_{it} = {} & \beta_0 + \beta_1\, App\ Launch_{it} + \beta_2\, Affected_i + \beta_3\, Post_t \\ & + \beta_4\, App\ Launch_{it} \times Post_t + \beta_5\, App\ Launch_{it} \times Affected_i \times Post_t \\ & + Controls + Firm\ fixed\ effects + Year\ fixed\ effects + \varepsilon_{it}. \end{aligned} \tag{4}$$

where Y_{it} is either $|Abnormal\ Investment_{it}|$ or $Inventory\ Turnover_{it}$, and $App\ Launch_{it}$ is our variable of interest, each as defined previously. $Affected_i$ identifies our treatment firms, i.e., firms with greater exposure to the consequences of privacy actions, while $Post_t$ identifies the post-privacy actions period. 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 and fixed effects are the same as in Equations (2) and (3), while standard errors are clustered by firm.

In all three cases, we expect that affected firms experience a relative decline in investment and inventory efficiency following privacy actions as a byproduct of a reduced ability to collect and use customer information. Thus, we expect to observe a positive (negative) estimated β_5 coefficient when the outcome variable is abnormal investment (inventory turnover).

4.3.1 General Data Protection Regulation

[7] The models include the full set of interactions. However, we drop some of the terms because they are redundant with the inclusion of fixed effects.

On May 25, 2018, the European Union's General Data Protection Regulation (GDPR) became effective. GDPR limited firms' ability to collect app users' 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 app user. Despite GDPR being an EU regulation, compliance is required for U.S. firms that collect or process data on EU citizens.[8] Research on GDPR has documented negative effects on data sharing by customers (Johnson, Shriver, and Goldberg 2022), web traffic and e-commerce sales (Aridor et al. 2022, Goldberg, Johnson, and Shriver 2022), and total sales and profitability (Chen et al. 2022).

We test our hypothesis that GDPR also resulted in less efficient investment and operating decisions by estimating Equation (4) above, where we define *Affected* as *HighEU%*, an indicator set to one if percentage of the app's total downloads that occurred in the EU is above the sample median, and zero otherwise; and *Post* as an indicator set to one if the firm's financial statements are released after the GDPR enforcement date (May 25, 2018), and zero otherwise. The coefficient of interest is β_5, 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 on |*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 operating efficiency.

[8] Maex (2022) finds that 29% 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).

The findings presented in Table 5, Columns (1) and (2), support our hypothesis. Firms with relatively more exposure to GDPR exhibit an increase in abnormal investment (Column (1): coeff. = 0.135; t-stat = 2.44) and a decrease in inventory turnover (Column (2): coeff. = -0.099; t-stat = -2.30) relative to firms with relatively less exposure to GDPR. The coefficient estimates suggest that affected firms experience a relative increase in abnormal investments of 14% and a relative decrease in inventory turnover of 10%.

4.3.2 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 investment and operating decisions by estimating Equation (4) above, where we define *Affected* as *California*, an indicator set to one if the firm's business address is located in California, zero otherwise, and *Post* as an indicator set to one if the firm's financial statements are released after the CCPA enforcement date (July 1, 2020), and zero otherwise.[9] The coefficient of interest is β_5, which captures the incremental effect of CCPA on firms with a mobile app located in California. We predict a positive (negative) coefficient on investment efficiency (inventory turnover), consistent with the argument that firms

[9] The exact locations of where firms generate their revenues is unobservable to us. For this reason, we rely on the assumption that firms generate relatively more of their revenues in the State of their business address. To the extent that this assumption is violated, then we would imprecisely identify affected firms and introduce attenuation bias (via measurement error) in our estimations.

that have less access to customer information from mobile apps following the enforcement of CCPA make less efficient decisions.

Table 5 Columns (3) and (4), where we report these estimations, lends support to this prediction. Following the enforcement of the CCPA, firms with a mobile app located in California exhibit a relative increase in abnormal investment of 35% (Column (3): coeff. = 0.346; t-stat = 1.69). However, we do not observe a statistically significant effect on inventory turnover (Column (4): coeff. = -0.055; t-stat = -0.82).

4.3.3 Privacy Nutrition Labels

In addition to specific regulations, 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 investment and operating 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, zero otherwise; and *Post* with an indicator variable that equals one if the firm's financial statements are released after Apple's App Store PNL requirements became effective (December 8, 2020), zero otherwise.

The coefficient of interest is β_5, which captures the effect of Apple's PNL disclosures on firms that collect relatively more data through mobile apps relative to firms that collect relatively less data. We find evidence consistent with our hypothesis. Table 5 reveals that firms that collect an above-median amount of data through their mobile apps in Apple Store experience a larger

[10] Google Play Store has also enacted similar policies. We do not examine the effects of Google Play Store's PNL policies because they were enacted late in our sample period and therefore, we do not observe a long enough post-implementation period.

decrease in investment efficiency (Column (5): coeff. = 0.250; t-stat = 3.14) and inventory turnover (Column (6): coeff. = -0.096; t-stat = -2.02) relative to firms that collect a below-median amount of data. These effects are economically significant as they indicate a relative increase in abnormal investment of 25% and a relative decline in inventory turnover of 10%.

Taken together, our evidence suggests that privacy regulations, which are intended to protect customers, produce the unintended effect of reducing the efficiency of investment and operating decisions by limiting the amount and quality of information available to firms. These results also help mitigate concerns that our findings in Tables 3 and 4 are driven by firms' selection into mobile app adoption and not the information channel we posit. The adoption of GDPR, CCPA, and PNL was largely outside of firms' control and independent of the operating and investment decisions of those firms, thus helping to rule out endogenous factors associated with mobile app use and to therefore make stronger conclusions about the effect of mobile apps on firms' information environments and decision making.

5. Additional Analyses

5.1 Why do Mobile Apps Help? Better Information versus More Stable Demand

There are at least two non-mutually exclusive ways in which the introduction of a mobile app would be associated with an improvement in investment and inventory efficiency. We predict that information obtained through mobile apps can lead to better forecasts of future demand (i.e., the information channel). However, it is also possible that mobile apps help to shape customer behavior in a way that makes future demand more predictable (i.e., the demand channel). While clearly separating the two channels is difficult because they are interwoven and endogenously determined, in this section we search for evidence to support one or both of the two 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:

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

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 $t+1$ divided by revenue in year t. We use the same controls as in Equation (3), as well as firm and year fixed effects.

If mobile apps make demand more stable or predictable, we expect to observe 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. Likewise, we expect to observe a positive β_3 coefficient when the outcome variable is *Revenue*$_{it+1}$, which indicates that mobile app adoption is associated with in more persistent revenues. We report estimated coefficients in the first two columns of Table 6. We fail to detect a significant decrease in revenue volatility (Column (1): coeff. = 0.008; t-stat = 0.29) or increase in revenue persistency (Column (2): coeff. = -0.045; t-stat = -0.62). This evidence indicates that the introduction of a mobile app is not associated with a 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:

$$Management\ Forecast\ Accuracy_{it} = \beta_0 + \beta_1 App\ Launch_{it} + Controls \\ + Firm\ fixed\ effects + Year\ fixed\ effects + \varepsilon_{it}, \tag{6}$$

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* represent other determinants of management forecast accuracy (Koo and Lee 2018). Importantly, these determinants include proxies for fundamental volatility such as sales and stock return volatility. Thus, we are holding, to the extent possible, fundamental uncertainty constant. We also include firm fixed effects and year fixed effects to control for 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 improves after a firm launches a mobile shopping app—both earnings forecast errors (Column (1): coeff. = -0.011; t-stat = -2.31) and revenue forecast errors (Column (2): coeff. = -0.014; t-stat = -1.67) decrease after the firm launches 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.

5.2 When do Mobile Apps Help?

In the previous sections, we have documented that mobile apps help firms make superior investment and operating decisions, and that this effect likely results from an information channel. In this section, we study under which conditions these effects arise.

5.2.1 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 et al. 2022). Absent this infrastructure, the firm may lack the tools to leverage the information provided by apps for investment and operating 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 operating decisions. 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. We expect the use of customer data for not just marketing decisions but also investing and operating decisions to be more likely in firms with superior internal information systems.

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.[11] We report coefficient estimates in Table 7, Panel A. The table shows that firms with high information system quality exhibit lower abnormal investment (Column (1): coeff. = -0.161; t-stat = -2.02, Column (5): coeff. = -0.054; t-stat = -1.69) and an increase in inventory turnover (Column (3): coeff. = 0.104; t-stat = 1.71, Column (7): coeff. = 0.044; t-stat = 1.65). On the other hand, we do not find any significant change in abnormal investment and inventory turnover for firms with lower information system quality. Furthermore, the difference in coefficients across the two subsamples is statistically significant at the 1% level for inventory turnover. Collectively, the results are consistent with firms with superior information system quality benefiting more from the launch of mobile apps.

5.2.2 Economic Conditions

The benefits of mobile app adoptions are likely heterogeneous across firms and over time. A general principle in decision theory is that information acquisition is more valuable when

[11] 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.

outcomes are more uncertain (Kacperczyk et al. 2016). Thus, we study whether the benefits of mobile app adoptions 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 those 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. The degree of product market competition is high when it falls below the median value and as low when it is above the median. Table 7 Panel B, which reports the associated estimates in Columns (1) to (4), lends support to our expectation. We find that firms with mobile apps operating in industries with high product market competition exhibit lower abnormal investment (Column (1): coeff. = -0.125; t-stat = -0.053) and higher inventory turnover (Column (3): coeff. = 0.058; t-stat = 0.035). On the other hand, we do not find any significant association between mobile apps and either abnormal investment (Column (2): coeff. = -0.006; t-stat = -0.026) or inventory turnover (Column (4): coeff. = 0.022; t-stat = 0.027) for firms facing low product market competition.

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% of the overall distribution of industry revenue growth. 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 = -0.027) and higher inventory turnover (Column (7): coeff. = 0.038; t-stat = 0.020). On the other hand, we do not find any significant association between mobile apps and either abnormal investment (Column (6): coeff. = 0.011; t-stat = 0.042) or inventory turnover (Column (8): coeff. = 0.025; t-stat = 0.030) for firms in industries that are not experiencing downturns.

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

5.3 How do Mobile Apps Help?

Having studied why and when mobile apps allow firms to make superior investment and operating 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. 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. These kits are packages that contain a set of tools that support features in a mobile app, including features that collect customer information, and should therefore allow for the collection of better and higher quality information. Consistent with this notion, we find in Table 8, Panel A, that the effect of mobile apps on both investment and inventory management 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 operating 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 reports the results from this investigation. We find that abnormal investment decreases following the launch of apps that collect customers' location or financial information (Column (1)). We also find that inventory turnover increases following the launch of apps that collect customers' financial information (Column (2)).

5.4 Robustness Tests

In this section, we assess the robustness of our main findings (Equations (2) and (3)) to alternative empirical choices. First, we assess whether our findings extend to alternative definitions of mobile app adoption that incorporate the quality of those apps. More specifically, we replace *App Launch* with *App Launch_Top3*, defined as an indicator sets to one if the three most rated apps for a firm are launched, and zero otherwise. Also, we replace *App Launch* with *IHS(#Raters)*, defined as inverse hyperbolic sine (IHS) transformation of the number of raters minus the mean number of raters among industry cohorts with the mobile app release in the same year. We apply IHS because the mean-adjusted number of raters can have zero or negative values

(MacKinnon and Magee 1990; Bahar and Rapoport 2018; Koo, Sivaramakrishnan, and Zhao 2023). Table A1 shows that in both cases, we continue to find that the efficiency of investment and inventory management efficiency increases for firms that release mobile apps.

Second, we assess whether our results extend to alternative industry definitions, which affect both the sample composition and the calculation of abnormal investments. Table A2 documents that our results continue to hold even in those cases.

Third, we verify whether our results hold if we proxy for investment efficiency with investment responsiveness to growth opportunities. Table A3 shows that whether we measure growth opportunities with Tobin's Q or revenue growth, firms' investment sensitivity to growth opportunities increases after firms release mobile apps, consistent with these firms experiencing lower levels of information uncertainty.

Fourth, we assess whether our findings are robust to alternative measures for the quality of firms' internal information systems. Table A4 confirms that the benefits of releasing mobile apps are concentrated among firms with superior internal information system quality, measured alternatively as whether a firm has reported a material restatement or a material weakness in the current fiscal year.

Finally, we test an alternative measure of economic conditions. In these tests, we switch to industry fixed effects instead of firm fixed effects because the sample shrinks considerably. We use product durability as an alternative measure for demand uncertainty because durable goods have more volatile cashflows (Gomes, Kogan, and Yogo 2009). Table A5, which reports the associated estimates in Columns (1) to (4), shows that investment efficiency increases for firms producing durable goods. We do not find any significant change in inventory turnover for both subsamples. Further, we consider a decline of over five percent in industry aggregate output as an alternative measure of industry downturn. Columns (5) to (8) of Table A5 confirms that the benefits of mobile apps are larger for firms in industries that are experiencing downturns.

6. Conclusion

Firms' success depends heavily on their ability to understand customers' needs and preferences. As such, information about their customers can represent a key ingredient to firms' 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 operating decisions, and whether privacy regulations 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 superior management forecasts and more efficient investment and production decisions. 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 show that customer privacy regulations can produce the unintended consequence of reducing the amount and quality of information available to firms when making investing and operating 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 regulations can harm the very individuals they were trying to protect. We also contribute to research on the implications of the internal information environment for managerial decision making and show that customer 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. Finally, we contribute to the literature on mobile apps. While marketing and information systems literature have examined the value of mobile app investment, 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$_{it}$	Indicator variable equal to one if an app was launched in or before year *t*, and zero otherwise.
|*Abnormal Investment*$_{it}$|	The 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$_{it}$	The 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$_{it}$	The 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$_{it}$	The 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$_{it}$	The logarithm of the cost of goods sold, scaled by average finished goods inventory, where average finished goods inventory is computed as the average of beginning and ending finished goods inventory.
Assets$_{it}$	The logarithm of total assets.
Age$_{it}$	The 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.
%Institutional$_{it}$	The percentage of shares held by institutional investors from Thomson Reuters 13f Holdings Database.
Revenue Volatility$_{it}$	The standard deviation of revenue (scaled by assets) for the previous 12 quarters.
Asset Turnover$_{it}$	Total revenue, scaled by total assets.
HighEU%$_{i}$	Indicator variable equal to one if a firm has at least one app serving high number of customers in the European Union compared to the median, and zero otherwise.
GDPR Enforcement$_{t}$	Indicator variable equal to one if firm's annual statement is launched after the GDPR enforcement date (May 25th, 2018), and zero otherwise.
California$_{i}$	Indicator variable equal to one if the firm's business address is located in California prior to CCPA enforcement period, and zero otherwise.
CCPA Enforcement$_{t}$	Indicator variable equal to one if firm's annual statement is launched after the CCPA enforcement date (July 1st, 2020), and zero otherwise.
High#Data_Apple$_{i}$	Indicator variable equal to one 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 zero otherwise.
Apple PNL$_{t}$	Indicator variable equal to one if firm's annual statement is launched after the apple IOS store's privacy nutrition label (PNL) requirements became effective (December 8th, 2020), and zero otherwise.
Revenue Volatility$_{it+1}$	The 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*$_{it}\|$	The 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$_{it}$	The 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$_{it}$	The 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$_{it}$	Indicator variable equal to one if a firm is identified as an IT leader in year t within the *InformationWeek* IT index, and zero otherwise.
CIO$_{it}$	Indicator variable equal to one if a firm's chief technology officer or chief information officer is on the board (identified through Boardex), and zero 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 the median.
Industry Downturn$_{it}$	Indicator variable equal to one if an industry's revenue growth is the bottom 33% of the overall distribution of median industry revenue growth, and zero otherwise.
High#SDKs$_{it}$	Indicator variable equal to one if a firm has at least one app with high number of software development kits (SDKs) compared to the median, and zero otherwise.
Location$_{it}$	Indicator variable equal to one if a firm has at least one app that collects users' location, and zero otherwise.
Contact$_{it}$	Indicator variable equal to one if a firm has at least one app that collects users' contact (e.g., e-mail address, phone number), and zero otherwise.
Personal$_{it}$	Indicator variable equal to one if a firm has at least one app that collects users' identity (e.g., name, ID), and zero otherwise.
Financial$_{it}$	Indicator variable equal to one if a firm has at least one app that collects users' financial information (e.g., payment, purchase), and zero otherwise.
Search$_{it}$	Indicator variable equal to one if a firm has at least one app that collects users' search history, and zero 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. Panel 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
$\lvert Abnormal\ Investment_{it}\rvert$	28,655	0.334	0.896	0.043	0.114	0.272
$Inventory\ Turnover_{it}$	22,855	2.652	1.253	1.663	2.402	3.511
$Inventory\ Turnover\_RM_{it}$	10,497	2.281	1.862	0.000	2.520	3.611
$Inventory\ Turnover\_WIP_{it}$	10,497	2.099	2.357	0.000	0.080	4.057
$Inventory\ Turnover\_FG_{it}$	10,497	2.229	1.396	1.293	2.084	3.064
$Assets_{it}$	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
$HighEU\%_{i}$	11,064	0.170	0.376	0.000	0.000	0.000
$GDPR\ Enforcement_{t}$	11,064	0.561	0.496	0.000	1.000	1.000
$California_{i}$	6,055	0.143	0.350	0.000	0.000	0.000
$CCPA\ Enforcement_{t}$	6,055	0.497	0.500	0.000	0.000	1.000
$High\#Data\_Apple_{i}$	6,055	0.080	0.272	0.000	0.000	0.000
$Apple\ PNL_{t}$	6,055	0.472	0.499	0.000	0.000	1.000
$Revenue\ Volatility_{it+1}$	30,087	0.137	0.174	0.030	0.073	0.165
$Revenue_{it}$	28,417	0.088	0.371	-0.039	0.044	0.146
$\lvert Earnings\ Forecast\ Error_{it}\rvert$	5,552	0.025	0.080	0.002	0.005	0.017
$\lvert Revenue\ Forecast\ Error_{it}\rvert$	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
$Restatement_{it}$	28,655	0.049	0.216	0.000	0.000	0.000
$Product\ Market\ Competition_{it}$	28,655	-0.821	0.452	-1.175	-0.876	-0.610
$Industry\ Downturn_{it}$	26,251	0.548	0.498	0.000	1.000	1.000
$High\#SDKs_{it}$	28,655	0.105	0.307	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

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	0.201
	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) |*Abnormal Investment*$_{it}$|	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 OLS regression results of residuals from investment model on mobile app launch. Column (1) reports the estimation results for the sample of 28,655 firm-year observations from 2006 to 2021. Column (1) reports the estimation results using the full sample. Columns (2) and (3) report the results after partitioning the sample based on whether the investment residuals are non-negative or negative. 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)**	**(3)**
Dependent Variable =		$\lvert$***Abnormal Investment***$_{it}\rvert$	
Sample =	**All**	**> 0**	**< 0**
App Launch$_{it}$	**-0.046****	**0.036**	**-0.082****
	(-1.88)	**(0.96)**	**(-2.37)**
Assets$_{it}$	0.005	-0.021	0.010
	(0.23)	(-0.76)	(0.39)
Age$_{it}$	0.010	-0.141*	0.167**
	(0.16)	(-1.63)	(2.01)
Leverage$_{it}$	-0.090**	-0.040	-0.068
	(-2.02)	(-0.43)	(-1.27)
#Analysts$_{it}$	0.002	-0.007**	0.009***
	(0.78)	(-1.98)	(2.85)
%Institutional$_{it}$	0.007	0.017	0.003
	(0.17)	(0.38)	(0.05)
Revenue Volatility$_{it}$	0.091*	0.165**	0.004
	(1.74)	(2.13)	(0.05)
Asset Turnover$_{it}$	-0.028	-0.091***	0.006
	(-1.19)	(-2.54)	(0.18)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
No. Observations	28,655	11,233	16,300
Adjusted R^2	14.0%	23.5%	14.4%

Table 4
Inventory Management Following the Launch of a Mobile App

This table reports OLS regression results of inventory turnover on mobile app launch. Column (1) reports the estimation results for the sample of 22,855 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. 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 =	***Inventory Turnover$_{it}$***	***Inventory Turnover_RM$_{it}$***	***Inventory Turnover_WIP$_{it}$***	***Inventory Turnover_FG$_{it}$***
App Launch$_{it}$	**0.039***	**0.167****	**-0.011**	**0.113****
	(1.83)	**(2.41)**	**(-0.11)**	**(2.03)**
Assets$_{it}$	0.108***	0.123**	0.295***	0.161***
	(4.73)	(2.09)	(4.13)	(3.71)
Age$_{it}$	-0.005	-0.007	-0.458***	-0.073
	(-0.10)	(-0.04)	(-2.67)	(-0.52)
Leverage$_{it}$	0.003	-0.070	-0.025	-0.125*
	(0.09)	(-0.87)	(-0.26)	(-1.78)
#Analysts$_{it}$	-0.004**	-0.017***	-0.010	-0.000
	(-2.15)	(-3.27)	(-1.41)	(-0.05)
%Institutional$_{it}$	0.035	0.142*	-0.042	-0.155**
	(1.11)	(1.72)	(-0.30)	(-2.15)
Revenue Volatility$_{it}$	0.111***	0.024	0.119	0.108
	(2.90)	(0.30)	(1.10)	(1.40)
Asset Turnover$_{it}$	0.312***	0.270***	0.272***	0.290***
	(10.30)	(4.30)	(3.73)	(5.41)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
No. Observations	22,855	10,497	10,497	10,497
Adjusted R^2	90.8%	84.4%	83.9%	81.4%

Table 5

Investment Efficiency and Inventory Management Following the Privacy Actions

This table reports OLS regression results of residuals from investment model and inventory turnover on mobile app launch following the privacy data disclosure mandates. 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). Each odd column reports the estimation results for investment efficiency and even columns report the estimation results for 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 =	$\lvert Abnormal\ Investment_{it}\rvert$	$Inventory\ Turnover_{it}$	$\lvert Abnormal\ Investment_{it}\rvert$	$Inventory\ Turnover_{it}$	$\lvert Abnormal\ Investment_{it}\rvert$	$Inventory\ Turnover_{it}$
$App\ Launch_{it}$	0.062	-0.014	0.117	0.038	0.209**	0.022
	(1.37)	(-0.28)	(1.17)	(0.64)	(2.06)	(0.36)
$Affected_i$	-0.010	0.095*	-0.030	-0.068	-0.428***	0.018
	(-0.11)	(1.62)	(-0.21)	(-0.47)	(-3.38)	(0.30)
$Post_t$	0.015	0.066	0.080	0.053	0.109	-0.035
	(0.23)	(0.58)	(0.58)	(0.75)	(1.25)	(-1.00)
$App\ Launch_t \times Post_t$	-0.143***	0.050	0.060	0.018	0.000	0.045**
	(-3.84)	(1.34)	(1.07)	(0.77)	(0.00)	(2.02)
$\boldsymbol{App\ Launch_t \times Affected_i \times Post_t}$	**0.135*** **	**-0.099** **	**0.346* **	**-0.055**	**0.250*** **	**-0.096** **
	(2.44)	**(-2.30)**	**(1.69)**	**(-0.82)**	**(3.14)**	**(-2.02)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	11,064	8,633	6,055	4,692	6,055	4,692
Adjusted R^2	22.8%	94.0%	25.3%	95.0%	25.3%	95.0%

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

This table reports the results of sales volatility, sales persistence, and earnings and revenue forecast errors as a function of app launch. Column (1) reports regression results of sales volatility on mobile app launch. Columns (2) A reports OLS regression results of next year sales 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***$_{i,t+1}$	$\lvert$***Earnings Forecast Error***$_{it}\rvert$	$\lvert$***Revenue Forecast Error***$_{it}\rvert$
App Launch$_{it}$	**0.008**	**0.009**	**-0.011****	**-0.014***
	(0.29)	**(0.85)**	**(-2.31)**	**(-1.67)**
Revenue$_{it}$	**.**	**0.076*****	**.**	**.**
		(3.81)		
Revenue$_{it}$ **×** ***App Launch***$_{it}$	**.**	**-0.045**	**.**	**.**
		(-0.62)		
Assets$_{it}$	0.064	-0.168***	0.002	-0.017**
	(0.74)	(-13.52)	(0.37)	(-2.33)
Age$_{it}$	-0.589*	-0.119***	-0.009	-0.025
	(-1.64)	(-3.94)	(-0.58)	(-0.88)
Leverage$_{it}$	0.137**	0.016	0.042***	0.106***
	(1.96)	(0.67)	(3.26)	(5.16)
#Analysts$_{it}$	-0.002	0.001	-0.000	-0.003***
	(-0.74)	(0.84)	(-0.70)	(-4.28)
%Institutional$_{it}$	0.006	0.008	-0.016*	-0.001
	(0.26)	(0.49)	(-1.71)	(-0.04)
Revenue Volatility$_{it}$	-0.342***	-0.029	-0.004	0.008
	(-2.55)	(-1.28)	(-0.41)	(0.42)
Asset Turnover$_{it}$	0.407**	-0.357***	0.004	-0.036***
	(2.08)	(-20.54)	(0.62)	(-2.92)
Earnings Forecast Horizon$_{ti}$	.	.	0.004***	.
			(5.23)	
Revenue Forecast Horizon$_{ti}$	.	.	.	0.016***
				(10.18)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
No. Observations	30,087	28,417	5,552	5,552
Adjusted R^2	42.3%	25.1%	71.2%	30.3%

Table 7
When do Mobile Apps Help?

This table reports OLS regression results of residuals from investment model and inventory turnover on mobile app launch using different sub-sample. 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**	**0.104***	**0.037**	**-0.054***	**-0.035**	**0.044***	**0.021**
	(-2.02)	**(1.59)**	**(1.71)**	**(1.15)**	**(-1.69)**	**(-0.91)**	**(1.65)**	**(0.63)**
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	Yes	Yes	Yes	Yes
No. Observations	521	14,848	414	12,077	13,310	15,025	8,909	13,691
adj. R^2	8.2%	7.3%	98.3%	93.0%	17.8%	15.9%	93.1%	90.0%
	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	<0.001		<0.001		0.392		0.010	

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**	**0.058***	**0.022**	**-0.046***	**0.011**	**0.038***	**0.025**
	(-0.053)	**(-0.026)**	**(0.035)**	**(0.027)**	**(-0.027)**	**(0.042)**	**(0.020)**	**(0.030)**
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
No. Observations	11,379	17,185	9,530	13,265	13,965	11,421	11,922	8,393
adj. R^2	20.0%	9.2%	89.4%	91.9%	10.2%	12.0%	92.4%	89.7%
	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		0.064		0.068		0.352	

Table 8
How do Mobile Apps Help?

This table reports OLS regression results estimating investment efficiency and inventory turnover as a function of different characteristics of app launch. 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 =	|*Abnormal Investment$_{it}$*|	*Inventory Turnover$_{it}$*
App Launch$_{it}$	**0.022**	**-0.025**
	(0.51)	**(-0.65)**
High#SDK$_{it}$	**-0.096****	**0.091****
	(-2.01)	**(2.07)**
Controls	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
No. Observations	28,655	22,855
adj. R^2	14.0%	90.8%

Panel B. Individual Mobile App Features

	(1)	(2)
Dependent Variable =	|*Abnormal Investment$_{it}$*|	*Inventory Turnover$_{it}$*
Location$_{it}$	**-0.156****	**0.001**
	(-2.30)	**(0.01)**
Contact$_{it}$	**0.076**	**-0.006**
	(1.32)	**(-0.12)**
Personal$_{it}$	**0.063**	**-0.012**
	(1.02)	**(-0.25)**
Financial$_{it}$	**-0.106****	**0.105****
	(-2.36)	**(1.95)**
Search$_{it}$	**0.085**	**-0.021**
	(1.42)	**(-0.30)**
Controls	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
No. Observations	28,655	22,855
Adjusted R^2	14.0%	90.8%

Online Appendix of

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Appendix OA
Variable Definitions

Variable	**Definition**
App Launch_Top3$_{it}$	Indicator variable equal to one if the three most rated apps for a firm are launched, and zero otherwise.
IHS(#Raters$_{it}$*)*	Inverse hyperbolic sine (IHS) transformation of number of raters minus the mean number of raters among cohorts with the same app release. (MacKinnon and Magee 1990; Bahar and Rapoport 2018).
Capex$_{it+1}$	Capital expenditures in year *t+1*, scaled by total assets in year *t*.
Tobin's Q$_{it}$	The sum of total assets and market value of equity minus book value of common equity, scaled by total assets.
Revenue Growth$_{it}$	Annual sales growth rate.
Restatement$_{it}$	Indicator variable equal to one if a firm restates in the past fiscal year due to error, and zero otherwise.
ICW$_{it}$	Indicator variable equal to one if a firm experienced internal control weakness in the past fiscal year, and zero otherwise.
Product Durability$_{i}$	Indicator variable equal to one (zero) when the firm is in the durable (non-durable) goods industry.
Large Drop in Industry Output$_{it}$	Indicator variable equal to one if an aggregate industry production drops more than 5%, and zero otherwise.

Table A1: Alternative App Launch Definition

This table reports OLS regression results estimating investment efficiency and inventory turnover as a function of alternative app launch indicators. Columns (1)-(2) report results when replacing the dependent variable with *App Launch_Top3*$_{it}$, which is an indicator variable that equals one if the firm has released one of the three most rated apps, and zero otherwise. Columns (3)-(4) report results when replacing the dependent variable with *IHS(#Raters)* is the Inverse hyperbolic sine (IHS) transformation of number of raters minus the mean number of raters among cohorts with the same app release. 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 and additional variables are defined in Appendix OA.

	App Launch_Top3$_{it}$		***IHS(#Raters***$_{it}$***)***	
	(1)	**(2)**	**(3)**	**(4)**
Dependent Variable =	***|Abnormal Investment***$_{it}$***|***	***Inventory Turnover***$_{it}$	***|Abnormal Investment***$_{it}$***|***	***Inventory Turnover***$_{it}$
App Launch$_{it}$	**-0.044***	**0.034*****	**-0.004****	**0.002****
	(-1.76)	**(2.98)**	**(-2.33)**	**(2.11)**
Controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
No. Observations	28,655	22,855	28,655	22,855
Adjusted R^2	14.0%	90.8%	14.0%	90.8%

Table A2

Alternative Industry Classification

This table reports OLS regression results of abnormal investments and inventory turnover on mobile app launch indicator, using different definitions of industry. Regressions include controls and fixed effects as indicated. Columns (1)-(2) limit the sample to Fama-French (48-classification) industries, where at least 10% of firms have released mobile apps. Column (1) uses the dependent variable (abnormal investments) measured based on Fama-French 48 industries. Columns (3)-(4) limit the sample to SIC 4-digit industries, where at least 10% of firms have released mobile apps. Column (3) uses the dependent variable (abnormal investments) measured based on SIC 4-digit industries. *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.

Industry Classification=	Fama French 48		SIC 4-digit	
	(1)	**(2)**	**(3)**	**(4)**
Dependent Variable =	***|Abnormal Investment$_{it}$|***	***Inventory Turnover$_{it}$***	***|Abnormal Investment$_{it}$|***	***Inventory Turnover$_{it}$***
App Launch$_{it}$	**-0.019****	**0.053****	**-0.028****	**0.038***
	(-2.06)	**(2.42)**	**(-2.03)**	**(1.86)**
Controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
No. Observations	31,380	24,776	21,959	31,425
Adjusted R^2	23.4%	89.3%	22.4%	87.9%

Table A3
Alternative Investment Efficiency Measures

This table reports OLS regression results of next year capital expenditure on mobile app launch, Tobin's Q (revenue growth), and their interactions, using the sample of 65,798 (70,398) firm-year observations from 2006 to 2021. 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 and additional variables are defined in Appendix OA.

	(1)	(2)
Dependent Variable =	***Capex***$_{it+1}$	
App Launch$_{it}$	0.003	0.007***
	(1.10)	(2.61)
App Launch$_{it}$ **×** ***Tobin's Q***$_{it}$	**0.002***	**.**
	(1.89)	
App Launch$_{it}$ **×** ***Revenue Growth***$_{it}$	**.**	**0.019****
		(2.12)
Tobin's Q$_{it}$	0.004***	.
	(6.44)	
Revenue Growth$_{it}$	.	0.002
		(0.54)
Assets$_{it}$	-0.047**	-0.049**
	(-2.03)	(-2.19)
Age$_{it}$	-0.013	-0.024**
	(-1.01)	(-2.21)
Leverage$_{it}$	-0.047*	-0.047*
	(-1.70)	(-1.69)
#Analysts$_{it}$	0.001	0.001
	(0.91)	(0.75)
%Institutional$_{it}$	0.024***	0.021***
	(2.57)	(2.94)
Revenue Volatility$_{it}$	-0.002	0.004
	(-0.27)	(0.55)
Asset Turnover$_{it}$	-0.004	-0.004
	(-1.09)	(-1.24)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
No. Observations	65,798	70,398
adj. R^2	4.3%	4.6%

Table A4
Alternative Internal Information System Quality Measures

This table reports OLS regression results of residuals from investment model and inventory turnover on mobile app launch using different sub-sample. Columns (1)-(4) report results based on whether the firm has made a restatement in the previous year. Columns (5)-(8) reports results based on whether the firm disclosed internal control weakness in the previous year. Variables are defined in Appendix A and additional variables are defined in Appendix OA.

	Restatements				**Internal Control Weaknesses (ICW)**			
	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$_{it}$	**0.314**	**-0.047*****	**-0.043**	**0.043******	**0.040**	**-0.039*****	**0.393**	**0.036*****
	(1.18)	**(-1.69)**	**(-0.35)**	**(2.00)**	**(0.28)**	**(-1.69)**	**(1.31)**	**(1.73)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
No. Observations	982	27,209	776	21,741	1,730	26,316	1,181	21,245
adj. R^2	3.7%	13.8%	94.3%	91.0%	24.4%	13.7%	84.8%	91.6%

	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	<0.001	<0.001	<0.001	<0.001

Table A5
Alternative Product Market and Economic Conditions Measures

This table reports OLS regression results of residuals from investment model and inventory turnover on mobile app launch using different sub-sample. Columns (1)-(4) report results based on whether the firm is in the durable goods industry. Columns (5)-(8) reports results based on whether the firm experiences a large drop in industry production. Variables are defined in Appendix A and additional variables are defined in Appendix OA.

	Product Durability				**Large Drop in Industry Output**			
	Nondurable	Durable	Nondurable	Durable	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$_{it}$	**0.020**	**-0.209****	**0.177**	**-0.051**	**-0.023****	**0.022**	**0.145****	**0.099****
	(0.026)	**(-0.106)**	**(0.111)**	**(-0.192)**	**(-0.010)**	**(0.018)**	**(0.071)**	**(0.044)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	No	No	No	No
No. Observations	1,311	3,346	1,409	2,151	1,948	27,268	2,045	21,275
adj. R^2	15.8%	11.3%	30.8%	42.6%	11.5%	8.8%	56.6%	44.8%
	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	<0.001		0.004		<0.001		0.004	