Rivalry, Market Structure and Innovation: The Case of Mobile Banking*

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Abstract

This paper focuses on a novel phenomenon—mobile banking diffusion—to analyze innovative behavior in the U.S. modern banking era. Using a unique, hand-collected dataset of mobile banking app adoption for 2008-2012, this study shows strong evidence that rivalry adoptions spur technological innovation. This effect increases monotonically with the degree of market concentration, and is the strongest in most concentrated markets, where banks compete on non-price attributes. These results are robust to the application of instrumental variables that address the possibility that adoptions are merely simultaneous reactions to the same common forces. Finally, the impact of mobile app adoption on bank performance is also examined.

Keywords: *Competitive Rivalry, Innovation, Market Structure, Mobile Banking, Technology Adoption*

JEL Classifications: *D43, G21, O14, O33*

I. Introduction

The prominent role of product market competition in spurring innovation has been the subject of a long line of research in the economic literature.[1] And yet, this topic area has generated an extraordinary amount of debate and disagreement. Theoretical models suggest rather mixed effects of the impact of competition on innovation (Aghion, et al., 2005). On the empirical side, existing studies document diverse and conflicting results, suggesting that a competitive market can either encourage or deter innovative activities.[2] Further, both theoretical and empirical literature on the relation between competition and technology adoption is limited (Milliou and Petrakis, 2011; p.515). Almost none of the prior work examines how rivalry adoptions, a proxy for dynamic competitive pressure, interact with market structure during the technology diffusion process. One exception is the research on the adoption of the Automated Teller Machines (ATMs) in the banking sector. Hannan and McDowell (1987) document that the positive role of peers' adoptions in ATM diffusion diminishes in more concentrated markets.

More than two decades after the ATM study, this paper focuses on a novel phenomenon—mobile banking technology—to investigate the joint role of prior adoptions and market structure in fostering future adoptions. Mobile banking has grown substantially in the last few years and has gained rising attention from financial intermediaries by virtue of the critical role of retail banking. Meanwhile, mobile applications, also called "mobile apps", catalyze its growth and remain as the superior mobile platform recently. Mobile apps create unique user experiences with rich interface capabilities for distributing banking services, and thus are better perceived as strategic technologies that enable banks to differentiate from their competitive peers.

This study uses a unique, hand-collected dataset of mobile app adoption from iTunes as a proxy for the adoption of mobile banking from July 2008 to June 2012. Specifically, I ask whether and how banks react to competitors' adoptions of apps, and whether the reactions depend on market structure. I use market

[1] See e.g., Mansfield (1968); Reinganum (1981); Hannan and McDowell (1984, 1987); Hernández-Murillo, *et al.* (2010);
[2] See e.g., Escuer *et al*. (1991); Hernández-Murillo, *et al.* (2010); Hannan and McDowell (1984, 1987); Saloner and Shepard (1995)

concentration levels, measured by Hirshman-Herfinhdal index (HHI), to proxy for the mode of competition. Intuitively, firm strategic interactions may differ substantially in markets with different features. For instance, markets with low concentration ratios are better characterized by competition in prices (Bertrand competition) and highly concentrated markets dominated by competition in quantities (Cournot competition). Milliou and Petrakis (2011) develop a theoretical model and show that Cournot competition encourages technology adoption by the second firm more than Bertrand competition. This is because technology adoption increases adopters' output and decrease peers' output, which is referred to as the *strategic effect*. Thus, their model suggests a positive strategic effect of adoptions by rivals under Cournot competition.[3] Along these lines, I argue that rivals' adoptions of mobile apps encourage potential adoptions more in concentrated markets than in competitive markets, primarily because the dominant strategic component of apps makes them more appealing under the non-price competition.[4]

Empirical work faces the challenge that a bank may well move to mobile banking not because a rival has done so, but rather because the two are subject to the same, partly unmeasured exogenous forces. I address this identification challenge by using rivals' deposit shares in other markets to predict rivals' adoption decisions. While rivals' deposit shares in other markets correlate with their incentives to adopt mobile apps, there is little reason to believe that outside deposit shares of competitors have a direct influence on the potential adopters in that market other than through rivals' strategic behavior.

Based on a total of 99,960 bank-quarter observations with 694 commercial banks that adopted mobile apps, the instrumented rivalry adoptions estimated in a Cox proportional hazard model show strong evidence that the propensity to innovate is affected by peers' strategic decisions. Further, the influence of rival precedence on the adoption of mobile apps depends on the degree of market concentration. Specifically, banks react more strongly to strategic rivals in more concentrated markets than in

[3] Milliou and Petrakis (2011) suggest a negative *strategic effect* under Bertrand competition, because prior adoptions decrease the market price level including the price of peers. However, this is unlikely the case for mobile app technology. In the current context, the positive *strategic effect* is diminished under Bertrand competition because banks are competing on price attributes.

[4] For instance, adopting rivals may be able to attract more customers from banks not having apps, and thus make adoptions appealing.

competitive markets. To cement the validity of the interpretation, I provide further evidence using subsamples sorted on HHI. The results uncover a monotonically increasing impact of rivalry adoptions on the likelihood of adoption across HHI quartiles, with the strongest impact in highly concentrated markets, where banks compete on non-price attributes. This finding supports the economic theory of the classic oligopolistic competition, in which firms are interdependent and most sensitive to rivals' non-price choices (Scherer and Ross, 1990, pp. 199).

Finally, I investigate the impact of mobile app adoption on bank performance. The evidence indicates first mover advantage in that mobile app adoption improves a bank's overall profitability by adopting early. The results show that a potential revenue source is deposit-related service charges. Mobile app adoption is also associated with higher advertising expenditures, more workers relative to assets, and increased labor costs, supporting the view that banks adopted mobile apps for strategic purposes. Finally, there is little evidence of changes in the branch intensity, suggesting that mobile banking, like the Internet channel, might be a complement to physical branches (DeYoung, Lang, and Nolle, 2007).

This research makes two major contributions. First, it employs a unique, hand-collected dataset to first study the latest banking technology diffusion—the adoption of mobile apps—to add to our understanding of the nature of firm interactions in the financial service sector, which has been received little attention in the innovation literature (Frame and White, 2004). Moreover, prior studies on financial innovations have almost exclusively relied on special survey data due to the scarcity of suitable data (e.g., Akhavein, Frame, and White, 2005).[5]

Second, this paper addresses the long-standing and unsettled question of the effect of rivalry on the adoption of a new technology in the banking industry. Research on the dynamic impact of competitive rivalry during waves of technology diffusion has been limited, mainly because empirically identifying the role of competitive pressure in adopting innovations is inherently difficult (Forman, 2005). Major hurdles include the quality of measurements and potential simultaneity problems. The present study addresses

[5] See Frame and White (2004) for an excellent literature review on the adoption of financial innovations

both issues—measurement and simultaneity—and establishes that the impact of strategic adoptions increase monotonically with the degree of market concentration. Interestingly, the classic study of ATM adoptions by Hannan and McDowell (1987) finds the opposite results. Plausibly, since ATMs are in large part a labor-saving technology, the adoption is more likely when firms are sensitive to peers' pricing moves (Arrow, 1962).

Taken together, this study illuminates that strategic rivalry needs to be taken into account when assessing the relation between competitive pressure and firms' innovative behavior. The results also highlight the differential impact of rivals' competitive strategies on adopting different types of technological products conditional on the mode of the competition, which might have implications for policy makers when trying to modify the nature of competitive environment to spur innovation.

The reminder of the paper is organized as follows. Section II describes the development of mobile banking. Second III reviews the relevant literature. Section IV develops the main hypotheses. Section V describes the data and methodology. Section VI presents the empirical results. Finally, Section VII concludes.

II. Mobile Banking

Mobile banking is defined as using a mobile phone to access financial accounts by means of a bank's web page, either through a mobile web browser, text messaging (SMS), or a mobile app, according to Federal Reserve (2012).[6,7] Mobile banking apps have proliferated since the appearance of iPhone apps in July 2008, when Bank of America was the pioneer adopter. The number of banks with an iPhone app more than tripled from 155 to 497 during 2011, and the trend continues to increase, as illustrated in Figure 1.

[6] Mobile banking is distinct from mobile payment techniques, such as Google Wallet and Paypal services, which enable users to make "tap payments" through a near field communication (NFC) chip installed in the smartphone (Federal Reserve, 2012).

[7] Mobile banking has attracted considerable attention from Federal Reserve, financial institutions and social media. In March 2012, Board of Governors of the Federal Reserve System reported the findings from an online survey conducted in December 2011 and January 2012, examining the use of mobile technology to access financial services and make financial decisions. It is reported that mobile phones and mobile Internet access are in widespread use.

By July 2012, the end of sample period, 694 out of 6,019 U.S. banks had introduced iPhone apps.[8] Table 1 presents the adoption rates by bank size and geographic region. As seen, banks with larger size are more likely to adopt, consistent with prior studies on technology adoption by banks. In terms of geographic distribution, the Southwest district exhibits the highest adoption rates of 16.7%, while the Midwest district has the lowest. When grouped by regional Federal Reserve District, banks under the jurisdiction of Boston, Dallas, or St. Louis Fed show the greatest propensities to develop mobile banking apps.

These observations raise an important question: what drive the mobile app adoptions by banks? Anecdotal evidence suggests that the fundamental goal of rolling out mobile offerings is to deepen customer relationships (*American Banker*, February 6, 2012), since mobile apps enable banks to develop divergent distribution channels and to deliver customized financial services, thus enhancing customer satisfaction and further stabilizing market shares.[9] With regards to functionalities, mobile apps mainly offer transactional-based services that are similar to Internet websites, ranging from account information to personal wealth management. One of the superiorities of mobile banking over online banking come from a special feature, the Remote Deposit Capture (RDC), which allows customers to deposit checks by snapping digital photos without going to a banking center. Recently, banks have started to monetize some of the mobile conveniences.[10] As such, adopting mobile apps allow banks to grow revenues more easily, while the impact of adoption on cost reduction is less clear. For example, banks may invest more on advertising to market their new mobile services, and may have to hire specialized employees to roll out and maintain the apps and to address security issues. In all, this novel phenomenon provides a good opportunity to examine the adoption of a strategic technology in the financial service sector.

[8] iTunes stopped disclosing newly launched banking apps around September, 2012. So the sample period ends in mid-2012.
[9] "Banks Seek Sticky Relationships from Mobile Apps", *American Banker*, February 6, 2012.
[10] "Mobile Banking Pricing Model Becomes Clearer As More Banks Charge Fees," *American Banker*, October 30, 2013.

III. Literature Review

The adoption of financial innovation has long been acknowledged as an important field of study, but only two dozen relevant studies in the banking industry were discovered by Frame and White (2004).[11] Moreover, the literature on market structure, competitive pressure and technology diffusion provides mixed empirical evidence. Saloner and Shepard (1995) document that higher market concentration spurs the adoption of ATMs by U.S. banks. However, Escuer *et al.* (1991) find that the speed of ATM adoption by Spanish banks is maximized at some intermediate level of market concentration. And yet, Akhavein, Frame, and White (2005) show little effect of market concentration on the adoption of Small Business Credit Scorings (SBCSs) by large U.S. banks. Further, Hannan and McDowell (1987) is the only empirical study that takes up the joint impact of market concentration and competitive rivalry on technology adoption. Using annual data, they find a weaker impact of rival precedence on ATM adoptions in more concentrated markets and argue that the failure to adopt a successful innovation might affect the survivability of firms more profoundly in competitive markets (Hannan and McDowell, 1987, p.164).

Surprisingly, theoretical literature that examines the impact of competitive pressure on innovation is quite silent on technology adoption. The only work is Milliou and Petrakis (2011), who capture the increase of competitive pressure by contrasting a Cournot market to a Bertrand market since markets featured with price competition (Bertrand competition) are more competitive than markets with non-price competition (Cournot competition) (Singh and Vives, 1984). They show that a Cournot market encourages the technology adoption by the second firm more than a Bertrand market. If so, then different combinations of the mode of competition and rival precedence might have different effects on future adoptions. Their work further draws attention to the possibility that rivalry adoptions do not generate equivalent impact on potential adopters in every market.

[11] After 2004, studies mainly focus on the Internet banking adoption (i.e., DeYoung, *et al*. (2007), and Hernández-Murillo, *et al.* (2010)), and the diffusion of credit scoring (Akhavein, *et al.* (2005); Bofondi and Lotti (2006)).

In sum, the empirical evidence regarding the impact of competitive pressure on technology adoption is ambiguous, which could be due to the drawbacks of competition proxies. In fact, previous studies measure the intensity of competition either by the market concentration ratios (HHI) or by the number of firms. Yet, it is quite arguable that high degrees of concentration are evidence of lack of effective competition (Dasgupta and Stiglitz, 1980). Another crucial source of competitive pressure could come from rivals' adoptions, which have received little attention in the existing literature. Hence, this paper builds on the work of Milliou and Petrakis (2011) and empirically examines how rivals' strategic behavior interacts with the market structure during the mobile banking diffusion.

IV. Hypotheses

This section formalizes adoption predictions with regards to market structure, rivalry adoptions, and the joint determination of the two. First, the role of market structure alone in the technology adoption is ambiguous. Dating back to Reinganum (1981), theoretical model suggests no economic reason to link the reward from innovation with the market structure. However, it is possible that banks in concentrated markets enjoy a stable customer base, which guarantees future demand for new products (Hall and Khan, 2002), and thus are more likely to innovate. Alternatively, low concentration levels are generally associated with intense competition, forcing banks to be differentiated in order to gain comparative advantage over their rivals. Therefore, I make no prediction concerning the effect of market concentration on mobile app adoption.

Rival precedence in the adoption process catches strategic interactions in the product markets. Since actions of a single firm affect the payoffs of the other firms, a firm's pre-adoption profit as well as its post-adoption profit may depend on the number of adopters, known as the *stock effects* (Karshenas and Stoneman, 1993). One can argue that the probability of adoption will fall as adoptions increase, because banks expect to capture smaller rents from the innovation. However, this may not be true for mobile app adoption. In the current context, it is more likely that banks adopting mobile apps to gain a competitive advantage, and thus a large number of adoptions might indicate increased potential gains at the expense of other banks. For example, as more banks adopt, not having apps would cause banks to lose customers. As such, even if the profitability is difficult to forecast, a large proportion of adoptions will drive favorable consideration to adopt (Mansfield, 1968). Hence, I hypothesize that rivalry adoptions *increase* the probability of adoption.

Further, firm interactions might depend on the mode of competition associated with the particular market structure. In the theory of the oligopolistic competition, firms are sensitive to rivals' non-price choices because they compete on non-price dimensions in highly concentrated markets (Scherer and Ross, 1990, p.199). Thus, observed market structure and the type of competition it promotes will condition how a firm reacts to the introduction of a new technology. Indeed, by contrasting Cournot (non-price) competition with Bertrand (price) competition to capture the effect of increased competitive pressure (Singh and Vives, 1984), Milliou and Petrakis (2011) show that Cournot competition encourages the adoption by the second firm more than Bertrand competition. The major reason is that under Cournot competition, a rival's adoption increases its output and decreases non-adopters' output, and thus technology adoption has a positive *strategic effect*.[12] These arguments lead to the principal hypothesis in this study: *the influence of mobile app adoptions by rivals on potential adopters is greater in concentrated (Cournot) markets than in competitive (Bertrand) markets.*

V. Data and Method

A. Sample

The adoption data were hand-collected from the iTunes Store under the finance category. iTunes records all the customers' reviews for each app and the review dates. Thus, the date of the first customer review can be an appropriate proxy for the app launch date. In addition to a bank's legal name, each app

[12] Milliou and Petrakis (2011) argue that there is a second effect, *output effect*, which states that the higher a firm's output the larger its gain from adopting a cost-reducing technology. *However, the strategic effect always dominates the output effect for the second adopter* (p.514). The *output effect* diminishes under Bertrand competition because the post-adoption profits do not increase much given the narrow profit margin. For Cournot competition, post-adoption profits might increase a lot for even small increase in output given the relatively greater market power.

discloses information such as the link of the institutional website and the range of services provided. I next went to each institution's webpage to obtain the information on the headquarter location in order to match the data on bank financials from the Call report. Finally, 694 mobile app adopters were commercial banks identifiable by the "find office" option available on the FDIC website.[13]

The reader may be wondering why this study only focuses on the data from iTunes. This is because there are numerous limitations to collect data from other app vendors.[14] Also, I use the adoption of the iPhone app as a proxy for the adoption of the mobile banking app technology because iTunes was the first app store in the market and is still in the leading position all over the world.[15] The following evidence supports that, if anything, banks tended to adopt iPhone apps prior to Android apps. To show that, I selected 553 iPhone-app adopters from my sample and gathered the adoption dates from Google Play using the same method as from iTunes. For banks that could not be found on Google Play or the date of the first feedback was unavailable, I did a short survey to these banks via either phone calls or online specialists.[16] Table A.1 in the Appendix lists 59 sample banks with detailed information on bank name, Federal Reserve identification number (RSSDID), adoption dates for iPhone app and Android app, survey method and testing results. Table 2 reports the results of banks' preference in choosing apps. As expected, only 5% of the 553 banks adopted Android apps first.[17] For these 5% banks, I corrected the adoption data with their Andriod app adoption dates to alleviate the measurement error problem. Overall, the results confirm that almost all of the banks with an iPhone app adopted Android apps no earlier than adopting iPhone apps.

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[13] This option is available at: http://www2.fdic.gov/sod/sodInstBranch.asp?barItem=1

[14] For example, Google's Android apps are comparable to iPhone apps. Unfortunately, in each Android app, only 48 pages of reviews are available. So the earliest customer review might not be available if a bank has above 480 reviews, which also indicates that the bank adopted Android app really early. I couldn't get data from Google after repeated requests.

[15] Google's Android market, Blackberry apps world, Nokia store, Windows Phone marketplace and Amazon app store were released 3 months, 10 months, 11 months, 29 months and 34 months later than the initial launch of Apple App store.

[16] Detailed selection criteria and survey method are discussed in Appendix A.

[17] I acknowledge that this methodology suffers sample selection biases. To the best of my knowledge, there is no complete information available on Google Play as to how many banks adopted Android apps since Google only lists 480 "bank" relevant apps.

In addition to the adoption data, information was gathered from three data sources. Call report data on bank financials were obtained from the Wharton Financial Institutional Center and the Federal Reserve Bank of Chicago website. Branch-level data on deposits and locations were collected from the Summary of Deposits from the FDIC website. Lastly, economic and demographic data were extracted from the Bureau of Labor Statistics.

B. Empirical Methodology

As with the case of other innovative technologies, banks face idiosyncratic short-run circumstances that influence the costs and benefits of adopting mobile apps. I thus employ a Cox proportional hazard model to examine the effects of rivalrous adoption and the market structure conditional on other covariates that might influence the adoption decisions. The model specifies a hazard rate taking the form:

$$h[t, x(t), \beta] = h_0(t) \exp[x(t)'\beta] \tag{1}$$

where $h[t, x(t), \beta]$, referred to as the hazard rate, is the probability that a bank developed a mobile app at time t given that it has not done so before time t. $x(t)$ is the vector of explanatory variables and β is a vector of parameters to be estimated. $h_0(t)$ is the baseline hazard rate without specific functional form. At each quarter t, β captures the effect of change in $x(t)$ on the relative risk of failure (probability of adoption). A positive coefficient suggests that an increase in the variable increases the hazard of adoption.

To reliably gauge the effect of competitive rivalry on mobile app adoption, I identify rival banks at the branch level to capture their geographical presence. For each quarter, I calculate *Local Rivals* as the percentage of rival banks that had introduced mobile apps in each market, and then weight the percentage by the deposit shares a bank has in each market. I define markets at the MSA level when a bank operates within an MSA, otherwise at the county level. Hence, *Local Rivals* dynamically capture the weighted average competitive pressure a bank faces throughout the investigation period. To proxy for the market structure, I compute the market concentration ratio, which is defined as the deposit-weighted sum of squared deposit shares of banks within each market and denoted as *HHI_Deposits*.

The vector $x(t)$ incorporates a host of control variables, MSA fixed effects and year fixed effects. The MSA fixed effects control for common time-invariant unobserved market characteristics that may have driven adoptions by both rivals and potential adopters. The year fixed effects account for transitory nation-wide factors, such as negative macroeconomic conditions, that could influence the likelihood of adoption. To mitigate the concern that there might be some other firm- or market- specific factors connected to the adoption decisions, I follow the literature on technology adoption in the banking industry (e.g., Akhavein, *et al.*, 2005; and Hernández-Murillo, *et.al.*, 2010) and include bank size, age, Tier 1 ratio (a control for financial health), share of core deposits (a proxy for retail focus), service revenue relative to deposits (a control for the profitability of the customer base), labor and salaries, worker per branch, branch intensity (controlling for current service delivery channels), advertising and marketing expenditures (a proxy for image focus), and asset growth. Further, loan loss provision, loan charge-offs and a dummy indicating whether a bank has received TARP funds are included to alleviate the possibility that adoption might be polluted by the stressful recession period. I also include the fraction of the population under age 20-34, job growth rate and wage level to control for local market conditions. These market variables are weighted by the deposit shares of a bank to construct bank-specific market-level variables, thus reflecting the average market conditions where the bank operates. All variable definitions and data sources are reported in Appendix B. Finally, to mitigate the effect of outliers, all controls are winsorized at the 1^{st} and 99^{th} percentiles.

Table 3 reports the summary statistics of all variables included in the empirical analysis. We see that mobile app adopters are significantly different from non-adopters in virtually all of the measured dimensions except for labor cost, asset growth and loan loss provision, demonstrated by the difference-in-means tests in the last column. It is at primary importance to note that the average percentage of rivals with mobile apps when adoptions occur is 33.51%, much higher than the mean rivalry adoptions for non-adopters (11.42%). Moreover, mobile app adopters are situated in significantly less concentrated markets than their counterparts.

Some of the control variables show evidence consistent with the extant literature. For example, banks that have adopted apps are substantially larger, earn greater revenue from the services on deposit accounts, more focus on advertising and marketing strategies, and locate in MSA areas with higher wage levels and healthier local economic conditions. Other covariates might be specific to the case of mobile banking technology. Banks that have less intensive branching networks are more likely to be adopters because these banks might prefer branchless delivery channels. They appear to have worse conditions than non-adopters, indicated by lower Tier 1 ratio, higher loan charge-offs and higher likelihood to receive TARP funds. Finally, the adoptions tend to occur in the markets with young adults populated, suggesting higher demand for such services from the youth. More detailed discussion will be presented in the result section.

C. Identification

Although the MSA fixed effects soak up the average effect of the unobserved market heterogeneity, it is still possible that some other time-varying market characteristics simultaneously determine adoptions by rivals and potential adopters. To tackle this simultaneity bias, I use an instrumental variables (IV) approach. Specifically, *Local Rivals* are instrumented by rivals' deposit shares outside of the market and a dummy indicating whether a bank is headquartered in an MSA. The main instrument, denoted as *Rivals' Outside-Market Deposit Shares*, is constructed as follows: for each quarter, I compute the deposit shares of rival banks out of the market for any given market, adjusting for the market shares of rival banks, and then weight by the deposit shares of each bank. Essentially, I extract the portion of rivals' decisions that are uncorrelated with potential adoptions within the market to explain these rivals' adoptions. While rivals' deposit shares in other markets affect their propensity to adopt, there is little reason to think that out-of-market attributes of competitors have a direct impact on future adoptions in that market other than through rivals' strategic behavior. In a similar vein, a bank's headquarter location determine its innovation incentives, but is unlikely to be directly associated with adoptions by other banks. Hence, these two variables are reasonably justified and should be valid instruments for *Local Rivals.*[18]

Even if the instrumental variables approach alleviates the concern about simultaneity of rivalry adoptions, this method does not fully resolve the simultaneous bias due to unobservable market characteristics. Note, however, I address this issue in three ways. First, the host of controls should capture a wide range of unobservable effects. Second, the incorporation of MSA fixed effects removes the time-invariant unobserved market heterogeneity that may lead to the increases in both rivalry adoptions and the probability of adoption. Third, I cluster the standard errors at the MSA level to account for potential time-varying correlations in unobserved factors that affect banks within the same MSAs.

VI. The Empirical Findings

A. The Influence of Rivalry and Market Structure on Mobile App Adoption – Main Results

This section reports the results obtained from the Cox proportional hazard model. Table 4 gives the odds ratios and t-statistics based on the heteroskedasticity-robust standard errors clustered by MSA. In column (1), the odds ratio of *Local Rivals* is greater than one and is significant at a 1% statistical level, indicating that the adoptions by rivals significantly increase a bank's incentives to offer a mobile app. The odds ratio of *HHI_Deposits* is smaller than one and significant at a 5% level, suggesting that banks operating in less concentrated markets exhibit a higher propensity to adopt. This result is consistent with studies on the Internet banking adoption (DeYoung, *et al.*, 2007). In column (2), I perform the test of joint effect of rivalry adoptions and market structure by interacting *Local Rivals* with *HHI_Deposits*. As hypothesized, the odds ratio on the interaction term is larger than one and significant at a 1% level, reflecting a stronger effect of rivalrous adoption in more concentrated markets.

Note, however, these results might be biased due to the simultaneity issue of rivalry adoptions. I thus apply the IV approach by regressing *Local Rivals* on *Rivals' Outside-Market Deposit Shares* and an MSA

[18] In the empirical analysis, I provide detailed identification tests to show the validity of the instruments.

dummy, while controlling for MSA fixed effects and year fixed effects, to get the predicted *Local Rivals*, which is then used in the estimation of the hazard model. The results are reported in columns (3) and (4) of Table 4. Column (3) shows that rivalry adoptions have an even stronger positive impact on adoption decisions, after largely eliminating the source of simultaneity bias. In terms of economic magnitude, a one-standard-deviation-increase in the percentage of rivalry adoptions translates into an 11.49%-increase in the odds of adoption, holding other things constant. This finding supports the notion that the adoption of a mobile service channel is a strategic, defensive move, in line with the phenomenon of Internet banking (Forman 2005; Hernández-Murillo, *et al.*, 2010, DeYoung, *et al.*, 2007). However, the odds ratio on *HHI_Deposits* becomes insignificant, implying that market structure alone has little predictive power on the likelihood of adopting a mobile app, which supports the conclusion of Reinganum (1981). This result is also consistent with the finding in Akhavein, Frame, and White (2005), who fail to discern any significant impact of market concentration on SBCS adoptions.

Of particular importance, column (4) of Table 4 shows that the odds ratio on the interaction term becomes larger in magnitude (increasing from 1.038 in column (2) to 1.098 in column (4)) and is statistically significant at a 1% level. Consequently, we obtain an even stronger conclusion that rival precedence has a significantly greater impact on adoption decisions of mobile apps in more concentrated markets. This result provides empirical evidence to the economic theory of the classic oligopolistic competition that firms tend to compete on non-price attributes when markets are highly concentrated (Scherer and Ross, 1990, pp.595). As mentioned, such adoption behavior differs remarkably from the findings in Hannan and McDowell (1987), possibly due to the mode of competition and the distinct nature of underlying technological products. As ATMs should be more attractive in competitive markets, banks have stronger reactions to rivals' low prices than those in concentrated markets (Arrow, 1962).

I also examine the effect of heterogeneity of participants and market environment on the rate of mobile app adoption. First, consistent with the literature, bank size *(lnassets)* positively predicts the likelihood of adoption, supporting the *rank effects* that larger banks are more likely to invest in technologies than smaller banks because of scale economics or low risk exposure (Karshenas and Stoneman, 1993; Hall and Khan, 2002).[19] Second, bank's financial condition, as proxied by the Tier 1 ratio, has a significant and negative effect on adoption incentives, suggesting that banks with worse financial conditions are more likely to be adopters; these banks might view mobile banking as a means of attracting new customers and improving performance. Third, the deposit-related service revenue (*Service Revenue*) positively and significantly determines adoption decisions, indicating that mobile apps are considered a retail strategy to improve service quality, and might be used to prevent the loss of high-valued customers. Fourth, banks that spend more on advertising and marketing expenditures exhibit a higher inclination to offer mobile financial products. This result suggests that bankers, who rely more on media channels to build brand reputation, believe that mobile apps will allow them to attract more image-based customers. Fifth, with respect to bank's distribution and service strategies, branch intensity *(Branch Intensity*) has an odds ratio that is significantly less than one, implying that banks that are less branch-focused prefer mobile banking, probably because their customers have lower demand for person-to-person contact services. This finding is also similar to the case of Internet adoption (Hernández-Murillo, *et al.*, 2010). Finally, the demographic and geographic variables shed light on the occurrence of adoptions due to some demand-side factors. Among the market characteristics, large population of young adults *(Young)* significantly promotes the proliferation of mobile apps, implying an intense demand for mobile banking services from the youth and revealing high adoption rates of such services among young customers (Federal Reserve, 2012).

One possible caveat of the analysis is that the sample period was the most disruptive in the U.S. banking industry due to the 2008 global financial crisis, which might contaminate the results. For instance, banks that were particularly hard hit by the financial meltdown might be too stressful to introducing mobile offerings. To account for the level of stress faced by banks, I include loan loss provision, loan charge-offs and a dummy indicating whether a bank has received TARP funds. The results show that the probability of adoption is negatively related with loan charge-offs, indicating that banks'

[19] See e.g., Schumpeter (1950), Hannan and McDowell (1984), Furst, *et al.* (2002), Hernández-Murillo, *et.al.* (2010), DeYoung, *et al.* (2007)

willingness to invest in new technologies were negatively affected by the financial crisis. However, the introduction of these controls does not materially change the main results.

For completeness, column (5) shows the results of the first stage IV regression. We see that both of the instruments are significantly associated with the percentage of rivalry adoptions. Moreover, the large R^2 (0.74) demonstrates that the instruments explain a substantial portion of the variation in rivalry adoptions in a given market, which mitigates the concern of weak instruments. Further, the test of overidentifying restrictions (Hansen J-statistics) reported in column (3) fail to reject the null that the instruments are valid.

B. The Joint Effect of Rivalry and Market Concentration on Mobile App Adoption – Robustness

B.1. Subsample Analysis

To assess the differential impact of rivalrous adoptions on potential adopters across markets, I sort the sample into *HHI_Deposits* quartiles, rebalanced quarterly. Next, I estimate the hazard model on each group and compare the estimates of *Local Rivals* across the quartiles. For brevity, only the odds ratios on *Local Rivals* are reported in Panel A of Table 5. Clearly, the effect of *Local Rivals* increases monotonically from the least concentrated markets to the most concentrated ones. Specifically, a one-standard-deviation increase in the proportion of prior adoptions results in a 15.11% (t-statistic = 15.38) increase in the likelihood of adoption by banks in the top quartile of HHI, which is three times as large as the impact of rivalry in the bottom quartile (odds ratio of 1.054 with a t-statistic of 2.44). Further, a Chow test rejects the equality of the four subgroups (p-value < 0.00), and a χ^2 test strongly rejects the null that these four estimates are not significantly different from each other (p-value < 0.00). In all, the evidence of rivalry interactions in the adoption of mobile apps is the strongest in most concentrated markets, where banks are predominately competing on non-price strategies. Hence, these findings further support the notion that future adoptions are determined jointly by rival precedence and market structure, and that the role of rivals in stimulating the adoption of non-price, strategic technology reinforces with market concentration.

Another sample splits worth investigating is MSA banks versus rural banks since banks located in MSAs are generally bearing more intensified competitive pressure than those in rural areas; and therefore, these banks might react differently to peers' strategies. To investigate whether the adoption pattern in MSAs is different from that in rural areas, I repeat the analysis on MSA banks, defined as those headquartered in MSAs, and on all other banks, classified into non-MSA banks. The estimates are reported in Panel B of Table 5. Before proceeding, the Chow test rejects the equality of MSA banks and non-MSA banks (p-value < 0.00). The main result indicates that the interactive effect is more pronounced among MSA banks but is not significant among non-MSA banks. The potential explanation is that there is not much variation in the degree of market concentration for rural banks due to the fact that rural banks are often located in a single county and/or often far apart (DeYoung *et al.*, 2007).

B.2. Size Effect of Large Rivals

One potential concern is that the observed results might simply pick up the size effect of large rivals. Indeed, theories have proposed both demand side and supply side factors to explain why large firms are more likely to engage in innovation activities (e.g., Schumpeter, 1950; Mansfield, 1968). If this dataset is prevalent with the case where large banks dominate in a number of markets, and if these dominant banks are the ones adopting the innovation first, then the results might reflect a pure size effect of large rivals in the diffusion of innovation instead of rivals' interaction with the market structure.

To empirically disentangle these independent effects, I construct two variables to be included in the analysis. First, I control for rivals' assets, defined as total assets of rivals with apps in any given quarter scaled by total assets of banks in the market, and weighted by the deposit shares of each bank. This variable measures the strength of rivals. Second, to further capture the dominant-fringe market structure, I construct deposit-weighted HHI based on bank assets, denoted as *HHI_Assets*. As reported in Table 6, the results are robust to the additions of rivals' assets (Column 1), *HHI_Assets* (Column 2), or both (Column 3), suggesting that size effect of rivals should have no bearing on the conclusions.

B.3. The Impact of Rivalry and Market Concentration on the Speed of Adoption

Finally, I investigate whether the preceding results hold for the timing of adoption by estimating a Tobit model. The dependent variable is *Time Since Adoption*, defined as the number of quarters that a bank had offered the mobile app as of 2012:Q2. The model is estimated on a cross-sectional data of 2008:Q2 with the instrumented *Local Rivals* as of 2012:Q2. Essentially, I examine the timing of adoption observed in 2012:Q2, while controlling for the pre-adoption characteristics using mid-2008 data. The results are reported in Table 7. The reported marginal effect is the change in the expected value of *Time Since Adoption* for banks that had adopted apps. As seen, the Tobit estimations generate a set of quantitatively similar results.

C. Mobile App Adoption and Bank Performance

Since research has shown that innovation is an important driver of productivity, a further question is whether mobile delivery channel has any economic and financial impact on banks' performance. Also, some anecdotal evidence suggests that mobile banking might enable banks to reduce costs by closing branches and replacing tellers (*American Banker*, September 10, 2012) and to earn additional fee revenue (*American Banker*, October 30, 2013).[20, 21] To fill in the curiosity, this sub-section examines whether the adoption of mobile apps improves banks' ROA, helps banks to attract more deposits or stabilize customer relationships, and allows banks to reduce branches or labor force. To do this, I focus on banks that adopted mobile apps and estimate an OLS regression taking the following specification:

$$Performance\ of\ Bank_{i,t} = \alpha + \beta_1 * POST\ ADOPT_{i,t} + \beta_2 * TIME\ SINCE\ ADOPTION_{i,t} + \beta_3 * X_{i,t-1} + \gamma_i + \gamma_t + \varepsilon_{i,t} \quad (2)$$

[20] *American Banker*, "Bankers Talk Bluntly About Closing, Streamlining Branches", September 10, 2012

[21] *American Banker*, " Mobile Banking Pricing Model Becomes Clearer As More Banks Charge Fees", October 30, 2013

where the first key variable is $POST\ ADOPT_{i,t}$, a dummy equal to one once bank *i* adopted a mobile app and zero otherwise, which captures the difference in performance before and after the adoption. To explore the first mover advantage, I include $TIME\ SINCE\ ADOPTION_{i,t}$, defined as the number of quarters a bank has provided an app in quarter t. The dependent variable is a vector of the performance measures including ROA, deposit-related service charges, deposits, advertising expenditures, branch intensity, number of workers and labor costs, all scaled by total assets. $X_{i,t-1}$ is a vector of lagged firm characteristics as controls, as I incorporated in the previous analysis. All regressions account for bank (γ_i) and year (γ_t) fixed effects to mitigate the issue of unobservable heterogeneity.

Table 8 presents the estimation results using 10,868 bank-quarter observations. The reported t-statistics are based on robust standard errors clustered by bank. Models (1) and (2) examine the profitability. The results show a positive but insignificant coefficient on *POST ADOPT*, and a significantly positive coefficient on *TIME SINCE ADOPTION*, suggesting that early adopters exhibit greater improvements in their ROA. This result supports the argument of first mover advantage in the technology diffusion literature. Model (2) examines the source of gains. The results suggest that the enhanced profitability might be achieved through the increased revenues from deposit-related service charges, in line with what has been found in the studies of Internet adoption (DeYoung, Lang, and Nolle, 2007). This finding implies that mobile apps might allow banks to earn additional revenue by improving the menu of services. As discussed, banks are motivated to offer mobile financial services with the hope of reducing customer attrition rate through building multi-product customer relationships. To evaluate this efficacy, model (3) investigates the condition of the deposit funding. As seen, the adoption fails to enable banks to attract more deposits. Another way to interpret the result is that adopters do not lose deposits after rolling out the mobile apps.

The next four columns shed light on how the adoption of mobile apps affects banks' operating expenditures. Model (4) shows that banks have incurred greater advertising and marketing expenses after the adoption; and this phenomenon is more pronounced among early adopters, supporting the idea that banks need to invest more on advertising to market their new mobile financial services. The examination on branch intensity in model (5) helps to determine whether mobile service channel can be viewed as a substitute or a complement to physical branches. I find that there is little evidence that banks decrease their branch intensity during the post adoption period, favoring the notion of mobile apps as a complement to branches. This result is contrary to the anecdotal evidence (*American Banker*, September 10, 2012) but similar to the case of online banking (DeYoung, Lang, and Nolle, 2007). Finally, banks have increased work force and labor costs subsequent to the adoption, possibly due to higher demand for specialized technology workers to address potential security issues of mobile platform, which are currently the most challenging tasks of mobile banking business mode. By and large, the adoption of mobile apps is associated with greater advertising and labor expenditures, implying that banks roll out mobile apps potentially for strategic reasons.

VII. Conclusions

Using a unique dataset on the first wave of mobile app adoption by 694 U.S. commerical banks, this work shows robust evidence that firms react strongly to rivals' adoptions in reaching decisions to innovate. The analysis reveals that banks' reaction to rivalry adoptions depends on the market structure. In particular, for the case of mobile banking, the impact of rival precedence upon potential adopters is the least in highly competitive markets (featured with Bertrand competition), is monotonically increasing with the level of market concentration, and is the strongest in highly concentrated markets (dominated by Cournot competition). This empirical evidence is consistent with the theoretical prediction by Milliou and Petrakis (2011) and supports the economic theory of the classic oligopolistic competition that firms tend to compete on non-price attributes when markets are highly concentrated (Scherer and Ross, 1990, pp.595). Moreover, consistent with Reinganum (1981), the role of market structure alone in promoting innovation is still uncertain, after correcting for a number of unobservable, simultaneous biases.

In summary, this paper has improved our understanding on how rival interactions in the technology adoption differ with market structure by presenting evidence that banks are more likely to adopt strategic innovations in response to competitive peers in concentrated markets. For policy implications, this paper identifies that rivalry adoption is an important source of competitive pressure during the diffusion process. It also hints on the complexity of the relationship between competition and innovation. Recognizing these perspectives may be helpful for policy makers attempting to promote innovation through altering competitiveness, as the effect of competitive pressure varies with the type of the innovation and also with the market environment. Last but not least, competition authorities and regulators might need to be cautious about employing the traditional measures of competition, such as market concentration ratio, to evaluate the intensity of competition of a market.

Appendix A

Table A.1 *Selected Testing Sample and Survey Respondence of iPhone App Adopters*

Year	Bank Name	RSSDID	Adoption Date		Testing Result	Survey Method
			iPhone	Andriod		
2008	Bank of America	480228	07/10/08	10/22/08	Apple First	
	IBC Bank	1001152	09/20/08		Apple First	
	CHASE BK USA NA	489913	12/15/08	11/10/10	Apple First	
	JPMorgan Chase Bank, NA	852218	12/15/08	11/19/10	Apple First	
2009	PNC Bank, N.A.	817824	01/31/09		Don’t Know	888-PNC-BANK
	Citibank, NA	476810	03/01/09	03/01/09	Same Time	Online Specialist
	Wells Fargo Bank, NA	451965	05/18/09	05/18/09	Same Time	1-800-869-3557
	Compass Bank	697633	07/26/09	07/26/09	Same Time	1-800-273-1057
	Amarillo National Bank	353555	09/01/09	07/10/12	Apple First	
	Discover Financial Services	30810	11/17/09		Don’t Know	1-800-347-7000
	National Bank of Arizona	1004368	12/06/09	09/12/11	Apple First	
	PeoplesBank	613400	12/07/09	11/02/10	Apple First	
	Amegy Bank	676656	12/08/09	08/27/11	Apple First	
	Zions First National Bank	276579	12/08/09	08/12/11	Apple First	
	WoodForest National Bank	412751	12/24/09	10/29/10	Apple First	
2010	Vectra Bank Colorado	933957	01/01/10	10/25/11	Apple First	
	Kleinbank mobile banking	303550	02/02/10		Apple Only	1-888-553-4648
	Bank of Bookhaven, MS	2877831	04/03/10	01/25/12	Apple First	
	First Bank of Conroe	685658	05/03/10	11/23/11	Apple First	
	The Peoples Bank, GA	454434	06/10/10		Apple Only	770.867.9111
	Peoples state bank of	326344	07/07/10	01/30/12	Apple First	
	Sterling National Bank, NY	64619	08/05/10		Apple Only	(212) 760-2031
	Paducah Bank	285740	09/02/10		Apple Only	270.575.5700
	Northwest	1002878	10/02/10		Apple Only	877-672-5678
	Lubbock National Bank	766258	11/01/10	09/14/12	Apple First	
	Tidelands Bank	3185485	12/01/10	04/13/12	Apple First	
2011	Rockland Trust/ mDeposit	613008	01/03/11	02/03/11	Apple First	
	National Bank of	775456	02/01/11		Apple Only	
	Umpqua mobile bank	143662	03/06/11	03/19/12	Apple First	
	FCNB mobile banking	11499	04/01/11	08/03/11	Apple First	
	MercMobile	2608754	05/01/11	06/10/11	Apple First	
	Enterprise Bank & Trust	1190476	06/01/11	10/01/12	Apple First	
	Community Bank	460033	07/01/11	09/18/11	Apple First	
	Alliance Bank	176464	08/01/11	10/18/11	Apple First	
	Catskill Hudson Bank	2132594	09/01/11	04/02/12	Apple First	
	Monument Mobile Bank	3336607	10/04/11	09/13/11	Same Time	
	Western National Bank	778466	11/01/11	01/20/12	Apple First	
	PointBank	844567	12/01/11	11/22/11	Same Time	

Table A.1 (Continued)

Bank Name	RSSDID	Adoption Date		**Testing Result**	Survey Method
		iPhone	Andriod		
Other Banks Surveyed					
Oakstar Bank	3374412	06/15/10		Apple Only	417.877.2020
Sterling National Bank, NY	64619	08/05/10		Apple Only	(212) 760-2031
Herget Bank	656649	10/13/10		Apple Only	(309) 347-1131
Cumberland Valley National	647218	11/05/10		Apple Only	800.999.3126
American Bank of Commerce	215662	11/10/10		Apple Only	(806) 775-5000
TSB-Texas Security Bank	3619216	11/09/10		Apple Only	469.398.4800
BOT Mobile Banking	340135	12/04/10		Apple Only	(866) 378.9500
CAPITAL ONE NA	112837	12/14/10		Apple First	1-877-442-3764
First Bank of Dalton Mobile	2349459	04/16/12	04/04/12	Same Time	706-226-5377
Hyde Park Bank Mobile	5331	04/17/12	04/13/12	Same Time	773.752.4600.
LBT mobile banking	767255	04/18/12	07/23/12	Apple First	417-682-3348
Hondo National Bank Mobile	77253	04/18/12		Apple Only	830-426-7218
Bank of Sunset Mobile	910239	04/20/12	08/21/12	Apple First	(337) 662-5222
the City National Bank Mobile	596062	04/24/12	05/15/12	Apple First	1-800-776-0541
Northwest Georgia Bank	712031	04/24/12	04/24/12	Same Time	706-965-3000
Falcon Bank Mobile Money	564557	04/24/12	09/18/12	Apple First	(956) 723-2265
Peoples Bank Magnolia	712648	04/26/12		Apple Only	(870)-234-5777
Oneunited Bank Mobile	935308	04/26/12	04/27/12	Same Time	(323) 290-4848
Ally Mobile Banking	3284070	04/26/12	04/27/12	Same Time	Online Specialist
Citizens Bank and Trust	767554	04/28/12	05/01/12	Same Time	(318) 375-3217
Centrue Mobile	457547	04/29/12	06/04/12	Apple First	1-888-728-6466

Appendix B: Variable Definitions and Sources

Variables	Definitions	Source
A) Firm Variables:		
lnassets	the log of total assets	Call Reports
lnage	the log of years since the establishment	Call Reports
Branch Intensity	branches per billion dollars of assets	Summary of Deposits
Worker Per Branch	number of employees per branch	Call Reports; Summary of Deposits
Labor Cost	salary and benefits over total assets (%)	Call Reports
Salary Per Worker	salary and benefits per employee (in thousands)	
Core Deposits	the ratio of consumer deposits over total assets (%)	Call Reports
Service Revenue	the ratio of deposit-related service revenue over total deposits (%)	Call Reports
Tier1	the ratio of tier1 capital over risk-weighted assets	Call Reports
Advertising	the ratio of advertising and marketing expenses per thousand dollars of assets	Call Reports
Dadmk	a dummy variable equals one if a bank has reported its advertising and zero otherwise in any given quarter [22]	Call Reports
Asset Grow	the annual assets growth rate	Call Reports
Loan Loss Provision	the ratio of loss provision over total loans (%)	Call Reports
Loan Charge Offs	the ratio of loan charge offs over total loans (%)	Call Reports
Tarp Receiver	an indicator coded with one once a bank has received TARP funds	Treasury Department
Time Since Adoption	the number of quarters that a bank had offered a mobile app as of 2012:Q2 in the Tobit model; the number of quarters that a bank has offered an app in quarter *t* in the OLS regressions	iTunes Store
B) Market Variables:*		
Local Rivals	deposit-weighted sum of percentage of rival banks with mobile apps in any quarter at each market where banks operate (%)	iTunes Store; Summary of Deposits
Rivals' Outside-Market Deposit Shares	the out-of-the-market deposit shares of rival banks with mobile apps in each market in any given quarter, deposit-share adjusted	iTunes Store; Summary of Deposits
HHI_Deposits	deposit-weighted sum of squared deposit shares of banks in each market	Summary of Deposits
HHI_Assets	deposit-weighted market concentration ratio measured by bank assets	Summary of Deposits
Rival_Assets	deposit-weighted sum of the proportion of rivals' assets in each market where banks operate (%)	Summary of Deposits
Young	deposit-weighted annual percentage of people age 20-34 in the local market (%)	Bureau of Labor Statistics
Area Wage	deposit-weighted average annual wage of the local market (in thousands)	Quarterly Census of Employment and Wages
MSA	a dummy variable equals one if a bank is headquartered in an MSA	Summary of Deposits
Job Grow	deposit-weighted annual employment growth rate of the local market (%)	Quarterly Census of Employment and Wages

* *Note:* All market variables are deposit-weighted sum of MSA-level conditions, reflecting the average market conditions where each bank operates. For banks located out of MSA, the market is defined at the county level.

[22] According to the Call Reports, advertising and marketing expenses are only need to be reported if they are above $25,000 or 3% of "other non-interest" expenses. Therefore, about one-third of the observations in the sample do not have advertising data.

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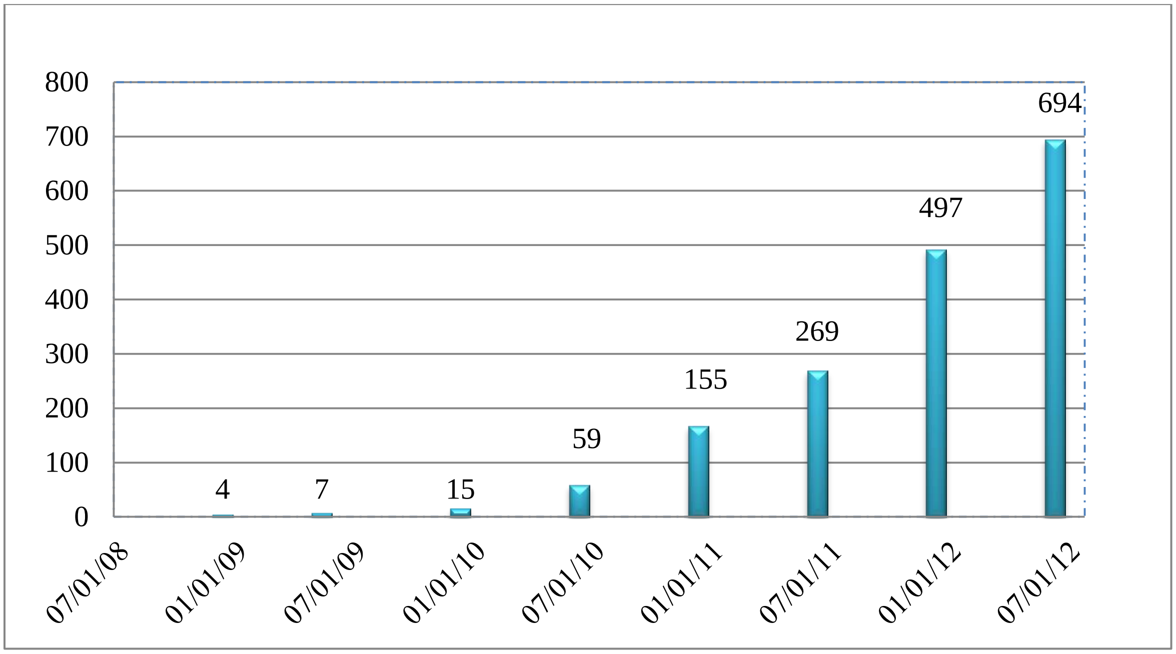
Figure 1 Cumulative Number of Banks that Adopted Mobile Apps over 2008:Q3-2012:Q2



Note. This figure shows the cumulative number of U.S. commercial banks that adopted mobile banking apps based on the data collected from iTunes Store.

Table 1 Size and Geographic Distribution of Mobile App Adoptions as of June 2012

	# of Adopters	# of Banks	Percentage
A.1 Size Distribution			
Assets< $1 billion	527	5,529	9.53%
$1 billion<= Assets< $5 billion	115	366	31.42%
Assets>= $5 billion	52	124	41.94%
A.2 Geographic Distribution By OCC District			
Central District	158	1,692	9.34%
Midwest District	141	1,822	7.74%
Northeast District	96	710	13.38%
Southwest District	299	1,795	16.66%
A.3 Geographic Distribution By Regional Fed			
Atlanta	113	784	14.41%
Boston	14	77	18.18%
Chicago	89	1,036	8.59%
Cleveland	34	246	13.82%
Dallas	101	597	16.92%
Kansas City	86	975	8.82%
Minneapolis	28	654	4.28%
New York	13	151	8.61%
Philadelphia	20	134	14.93%
Richmond	45	317	14.20%
San Francisco	41	400	10.25%
St. Louis	109	648	16.82%
Total	694	6,019	100%

Note. This table presents the adoptions by bank size and geographic locations as of June 2012.

Table 2 Which Apps Were Adopted by Banks First? Android Apps or iPhone Apps?

	Android apps Adopted FIRST					*Both* apps Adopted at Same Time	*iPhone* apps Adopted FIRST	Total testing samples
Month	<-4	-4	-3	-2	-1	0	≥1	
Number of Banks	4	5	5	6	5	**159**	**369**	553
Percentage	0.72%	0.90%	0.90%	1.09%	0.90%	**28.75%**	**66.73%**	100%

Note. This table compares iPhone app adoption and Android app adoption by banks from 2008:Q3 to 2012:Q2 based on 553 testing samples, for which I gathered adoption dates from Google Play using the same method as from iTunes.[23] For banks that could not be found by searching on Google Play, I did a short survey via either phone calls or online specialists to get the adoption information.[24] The table reports the number of banks adopted Android apps (iPhone apps) prior to iPhone apps (Android apps) and the number of banks adopted both apps around the same time. The corresponding percentages are also provided. Banks adopted both of the apps at the same time if the time lags between adopting Android apps and adopting iPhone apps are within two weeks. Table also shows the breakdown of the time lag of adopting Android apps earlier than adopting iPhone apps into 1 month, 2 months, 3 months, 4 months and more than 4 months. As illustrated, only 5% of these banks adopted Android apps first. For these banks, I corrected the adoption data accordingly.

[23] Testing samples include all banks adopted iPhone apps in 2008, 2009 and the first half year of 2012. For 2010 and 2011, I picked up the first adopters in each month and also adopters from January to March, June to July, and October to December. Therefore, the testing samples are covering the whole sample period.

[24] I asked two questions. First, whether the bank provided mobile apps besides iPhone app. If yes, which one did the bank adopt first? I have made 29 phone calls and talked to two online specialists. Six of them chose iPhone apps before Android apps, nine of them only have iPhone apps, eight of them provided both iPhone apps and Android apps at the same time, two of them didn't know, and the rest didn't answer the phone. For no answers, there was no disclosure of Android app adoption on the bank's website.

Table 3 Descriptive Statistics--Bank and Market Characteristics over 2008:Q3- 2012:Q2

	Adopters (Obs=694)				Non-Adopters (Obs=99,291)				Difference -in-means
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	
Key Variables:									
Local Rivals (%)	33.51	18.48	2.15	100.00	11.42	13.27	0.00	87.50	22.08***
HHI_Deposits	0.19	0.10	0.05	0.84	0.21	0.13	0.05	1.00	-0.02***
Control Variables:									
Assets ($mil)	11,418	98,036	32	1,746,242	875	11,853	3	1,768,657	10,543***
lnassets	13.27	1.30	10.39	16.06	11.96	1.19	9.62	16.06	1.30***
lnage	3.94	0.99	1.10	4.99	3.85	1.08	1.10	4.99	0.08**
Tier1	0.14	0.04	0.05	0.38	0.16	0.07	0.05	0.46	-0.01***
Core Deposits (%)	7.45	7.00	0.21	32.38	9.63	7.15	0.21	32.38	-2.18***
Service Revenue (%)	0.26	0.22	0.00	1.02	0.22	0.20	0.00	1.02	0.04***
Labor Cost (%)	1.02	0.56	0.20	2.75	1.00	0.56	0.20	2.75	0.03
Salary Per Worker	42.30	21.80	9.88	103.10	38.62	20.58	9.88	103.10	3.67***
Worker Per Branch	16.68	9.64	4.44	56.00	13.21	7.91	3.67	56.00	3.47***
Advertising	0.38	0.34	0.00	1.70	0.28	0.35	0.00	1.70	0.10***
Dadmk	0.81	0.40	0.00	1.00	0.65	0.48	0.00	1.00	0.15***
Branch Intensity	19.26	12.09	2.57	101.16	26.92	17.76	2.57	101.16	-7.66***
Asset Grow	0.01	0.05	-0.10	0.26	0.02	0.20	-0.10	0.26	-0.005*
Loan Loss Prov (%)	0.58	0.83	-0.06	5.33	0.56	0.92	-0.06	5.33	0.02
Loan Charge Offs (%)	0.62	0.83	0.00	4.88	0.51	0.86	0.00	4.88	0.11***
Tarp Receiver	0.25	0.43	0.00	1.00	0.10	0.30	0.00	1.00	0.15***
Young (%)	20.18	3.36	11.59	31.36	18.81	3.67	11.59	31.36	1.37***
Job Grow (%)	3.48	1.81	-6.13	10.28	2.08	3.03	-6.13	10.28	1.39***
Area Wage ($1,000)	41.47	8.72	23.44	66.83	38.65	9.16	23.44	66.83	2.82***
MSA	0.67	0.47	0.00	1.00	0.52	0.50	0.00	1.00	0.15***

Note. This table reports the summary statistics for the potential determinants of mobile app adoption for 694 adopters and 99,291 non-adopter observations from 2008:Q3 to 2012:Q2. All controls are winsorized at 1st and 99th percentiles. Difference-in-means tests are reported in the last column.

Table 4 The Effects of Rivalry and Market Concentration on the Probability of Adoption

Variables:			Instrumental Variables			
			Second-stage		Dependent Variable:	First-stage
	(1)	(2)	(3)	(4)	Local Rivals	(5)
Local Rivals	1.0735***	1.0630***	1.1149***	1.0901***	Rivals' Outside Deposit shares	0.5496***
	(43.90)	(13.36)	(7.49)	(5.89)		(178.41)
HHI_Deposits	0.4554**	0.0949**	0.8393	0.0978**	MSA	-1.1915**
	(-2.03)	(-2.13)	(-0.75)	(-2.55)		(-2.40)
Rival*HHI_Deposits		**1.0380****		**1.0979*****	Constant	7.7200***
		(2.10)		**(2.91)**		(26.77)
lnassets	2.0320***	2.0326***	1.9501***	1.9579***		
	(26.06)	(26.13)	(24.42)	(24.85)		
lnage	1.0933	1.0856	1.0997	1.0932		
	(1.49)	(1.46)	(1.46)	(1.42)		
Tier1	0.0345***	0.0324***	0.0380***	0.0404***		
	(-5.11)	(-5.39)	(-5.00)	(-4.89)		
Core Deposits	1.0060	1.0059	1.0058	1.0063		
	(1.19)	(1.18)	(1.15)	(1.25)		
Service Revenue	4.7913***	4.8734***	7.0752***	7.2139***		
	(6.70)	(6.52)	(5.96)	(5.93)		
Labor Cost	1.1862	1.1975	1.2959	1.2842		
	(1.03)	(1.10)	(1.62)	(1.55)		
Salary Per Worker	0.9989	0.9991	1.0010	1.0013		
	(-0.25)	(-0.21)	(0.20)	(0.26)		
Worker Per Branch	1.0085	1.0082	1.0030	1.0035		
	(0.72)	(0.70)	(0.30)	(0.35)		
Advertising*Dadmk	1.2485*	1.2505*	1.2910**	1.2999**		
	(1.82)	(1.83)	(2.22)	(2.27)		
Dadmk	1.3414***	1.3324***	1.3273***	1.3252***		
	(3.71)	(3.63)	(3.62)	(3.62)		
Branch Intensity	0.9839**	0.9840**	0.9764***	0.9767***		
	(-2.22)	(-2.19)	(-4.50)	(-4.42)		
Asset Grow	0.7190	0.7231*	1.0286	0.7077		
	(-1.63)	(-1.66)	(0.05)	(-1.58)		
Young	1.0366***	1.0364***	1.0422***	1.0404***		
	(2.96)	(2.96)	(3.22)	(3.10)		
Job Grow	1.0138**	1.0160**	1.0000	1.0020		
	(2.10)	(2.45)	(-0.01)	(0.27)		
Area Wage	1.0109	1.0085	0.9628***	0.9623***		
	(1.63)	(1.15)	(-5.44)	(-5.71)		
Loan Loss Provision	1.1020*	1.0980	1.1102*	1.1127*		
	(1.68)	(1.64)	(1.87)	(1.91)		
Loan Charge Offs	0.7815***	0.7834***	0.8017***	0.7965***		
	(-3.61)	(-3.58)	(-3.11)	(-3.23)		
Tarp Receiver	1.1680*	1.1767*	1.1921*	1.1846*		
	(1.68)	(1.73)	(1.83)	(1.77)		
MSA Fixed Effects	Yes	Yes	Yes	Yes		Yes
Year Fixed Effects	Yes	Yes	Yes	Yes		Yes
N	99,960	99,960	99,960	99,960		99,994
R^2						0.7401
Log pseudolikelihood	-4843.52	-4841.83	-5002.1861	-4999.55		
Hansen J (p-value)			0.51			
Durbin-Hausman-Wu			0.00			

Note. This table reports Cox proportional hazard estimates investigating the conditional probability of mobile app adoption. Models (3) and (4) report the estimates using an IV approach, where *Local Rivals* are instrumented by rivals' deposit shares outside of the market and a dummy indicating whether a bank is headquartered in an MSA. IV diagnostic statistics for overidentification restrictions and exogeneity conditions are also reported. Model (5) shows the coefficients of the first-step estimation of *Local Rivals* on the two instruments. All variables are defined in Appendix B. T-statistics based on heteroskedasticity-robust standard errors clustered by MSA are listed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5 The Joint Effect of Rivalry and Market Concentration on Mobile App Adoption (Subsample Analysis)

Panel A. the Increasing Effect of Rivals' Adoptions on Mobile App Adoption across HHI Quartiles

Variables:	HHI Q1 (1)	HHI Q2 (2)	HHI Q3 (3)	HHI Q4 (4)
Local Rivals	**1.0544****	**1.1075*****	**1.1382*****	**1.1511*****
	(2.44)	**(4.60)**	**(9.11)**	**(15.38)**
Full set of controls	Yes	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
N	24,860	25,070	25,035	24,995
Log pseudolikelihood	-995.52	-1060.90	-1255.55	-1002.57
Chow Test of the differences of subgroups	F-statistics=2.06; p-value=0.00			
Joint Test of the differences in the coefficients on *Local Rivals*	$\chi^2(3)$=45.63; p-value=0.00			

Panel B. MSA versus non-MSA Banks

Variables:	MSA Banks	Non-MSA Banks
	(1)	(2)
Local Rivals	1.0187	1.1168***
	(1.31)	(4.48)
HHI_Deposits	0.0028***	0.2982
	(-3.20)	(-0.75)
Rivals*HHI_Deposits	1.1911***	1.0911
	(2.87)	(1.30)
Full set of controls	Yes	Yes
MSA Fixed Effects	Yes	No
Year Fixed Effects	Yes	Yes
N	51,613	48,357
Log pseudolikelihood	-4523.69	-2114.61
Chow Test of the differences of subgroups	F- statistics =3.55; p-value=0.00	

Note. This table reports additional results of the Cox proportional hazard estimation investigating the conditional probability of mobile app adoption. In all models, *Local Rivals* are the predicted values using IV approach reported in Table 4. Panel A examines the effect of rivalry adoptions on mobile app adoption across HHI quartiles. Panel B shows the results of subsamples split by MSA banks and non-MSA banks. Chow tests of the differences of subgroups and joint tests of the differences in the coefficients are also presented. All specifications include the same set of control variables as in Table 4. All variables are defined in Appendix B. T-statistics based on heteroskedasticity-robust standard errors clustered by MSA are listed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 6 The Joint Effect of Rivalry and Market Concentration on Mobile App Adoption (Controlling for the Size Effect of Large Rivals)

Variables	(1)	(2)	(3)
Local Rivals	1.0913***	1.0912***	1.0934***
	(5.62)	(6.13)	(5.87)
HHI_Deposits	0.0868***	0.0957**	0.0759***
	(-2.60)	(-2.58)	(-2.74)
Rivals*HHI_Deposits	**1.1017*** **	**1.0965*** **	**1.1020*** **
	(2.99)	**(2.85)**	**(2.99)**
Rival_Assets	0.9990		0.9984
	(-0.80)		(-1.37)
HHI_Assets		1.1726	1.2501
		(1.05)	(1.50)
Full set of controls	Yes	Yes	Yes
MSA Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	99,960	99,960	99,960
Log pseudolikelihood	-4999.4821	-4999.4065	-4999.231

Note. This table reports additional robustness checks of the Cox proportional hazard estimation investigating the conditional probability of mobile app adoption. In all models, *Local Rivals* are the predicted values using IV approach reported in Table 4. Models control for the size effect of large rivals by incorporating rivals' assets, defined as total assets of rivals with apps in any given quarter scaled by total assets of banks in the market, and weighted by the deposit shares of each bank. *HHI_Assets* is the deposit-weighted HHI based on bank assets, which is included to capture the dominant-fringe market structure. All specifications include the same set of control variables as in Table 4. All variables are defined in Appendix B. T-statistics based on heteroskedasticity-robust standard errors clustered by MSA are listed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 7 The Impact of Rivalry and Market Concentration on the Timing of Adoption (Tobit)

Variables:	Full Sample	Subsamples by HHI Quartiles				Subsamples by MSA	
		HHI Q1	HHI Q2	HHI Q3	HHI Q4	MSA	Non-MSA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Local Rivals	0.0947*	0.0004	0.1545***	0.2176***	0.3201***	0.0355	0.2636***
	(1.88)	(0.01)	(3.21)	(4.18)	(15.38)	(0.84)	(4.19)
Rivals*HHI_Deposits	**0.2730*** **					0.3413**	0.1042
	(3.10)					(2.46)	(0.60)
HHI_Deposits	-10.9561***					-20.858***	-0.5130
	(-2.79)					(-3.60)	(-0.11)
lnassets	2.6205***	3.0912***	3.0480***	2.2147***	1.7784***	2.7375***	2.0402***
	(12.65)	(7.64)	(7.55)	(5.68)	(11.72)	(10.95)	(6.55)
lnage	-0.1679	-0.7437**	-0.3689	0.1808	0.7319**	-0.2484	0.2382
	(-0.95)	(-2.34)	(-1.30)	(0.52)	(2.32)	(-1.06)	(0.67)
Tier1	-0.6860	-0.7722	4.6016	-2.8450	-17.29***	1.1107	-10.8450**
	(-0.25)	(-0.13)	(1.29)	(-0.38)	(-7.01)	(0.34)	(-2.20)
Core Deposits	-0.0166	0.0263	0.0236	-0.1117**	-0.0251	-0.0220	-0.0297
	(-0.60)	(0.36)	(0.44)	(-2.25)	(-1.00)	(-0.48)	(-0.66)
Service Revenue	5.1052***	1.7333	6.0431***	7.6483***	6.2472***	4.3809***	6.0608***
	(7.97)	(1.15)	(4.36)	(6.34)	(10.45)	(4.81)	(4.55)
Labor Cost	1.1807**	2.6138***	0.9376	0.2120	-0.6724	0.9014	1.2794
	(2.44)	(2.75)	(0.99)	(0.17)	(-0.41)	(1.53)	(1.09)
Salary Per Worker	-0.0442**	-0.0930***	-0.0178	0.0466	-0.0807*	-0.0153	-0.1057***
	(-2.04)	(-3.28)	(-0.40)	(1.49)	(-1.75)	(-0.75)	(-2.58)
Worker Per Branch	0.0110	-0.0599**	0.0341	0.0147	0.0762	-0.0009	0.0038
	(0.52)	(-2.01)	(0.88)	(0.27)	(1.37)	(-0.04)	(0.06)
Advertising*Dadmk	1.2770***	1.1328*	1.3850**	-0.0584	2.1949***	1.3054***	0.6936
	(3.68)	(1.72)	(2.31)	(-0.08)	(3.25)	(2.90)	(0.87)
Dadmk	0.1515	0.8565	0.3350	-0.4182	-0.0780	0.2785	0.0513
	(0.42)	(1.12)	(0.36)	(-0.54)	(-0.14)	(0.47)	(0.07)
Branch Intensity	-0.0559*	-0.0880**	-0.0060	-0.0481	-0.0962*	-0.0213	-0.1313***
	(-1.91)	(-2.32)	(-0.26)	(-1.09)	(-1.74)	(-0.98)	(-3.22)
Asset Grow	3.0941	3.4927	7.1809	-3.0341	-1.9938	6.0529*	-9.0630*
	(0.96)	(0.82)	(1.32)	(-0.47)	(-0.92)	(1.86)	(-1.85)
Young	0.0784*	0.0673	-0.0433	0.1689**	-0.0217	0.0481	-0.0130
	(1.69)	(0.68)	(-0.41)	(2.13)	(-0.57)	(0.68)	(-0.14)
Job Grow	0.1222	0.6632***	0.1527	-0.0100	0.0363	0.4690***	-0.0267
	(1.11)	(3.29)	(0.71)	(-0.11)	(1.61)	(3.27)	(-0.36)
Area Wage	-0.0728**	-0.0978*	-0.0712**	-0.0905*	-0.0408	-0.1177***	-0.0248
	(-2.21)	(-1.87)	(-2.08)	(-1.80)	(-0.76)	(-3.77)	(-0.42)
Loan Loss Provision	0.4820	0.2344	0.3512	-0.4345	0.4942	0.3898	-0.1077
	(1.16)	(0.29)	(0.44)	(-0.34)	(1.31)	(0.76)	(-0.10)
Loan Charge Offs	-0.7593	0.0180	-0.5367	-0.7550	-0.8166*	-0.1617	-1.1890
	(-1.38)	(0.02)	(-0.45)	(-0.66)	(-1.95)	(-0.26)	(-1.04)
N	5,735	1,392	1,367	1,466	1,510	2,846	2,889
Pseudo R^2	0.1271	0.1024	0.1376	0.1608	0.1632	0.1109	0.1554
Chow Tests of the differences of subgroups		By HHI Quartiles: F-statistics=2.39; p-value=0.00				By MSA:F-statistics=4.44; p-value=0.00	
Joint Tests of the differences in the coefficients on *Local Rivals*		$\chi^2(3)$=17.40; p-value=0.00					
Marginal Effects of key variables							
Local Rivals	0.0145*	0.0001	0.0241***	0.0318***	0.0409***	0.0063	0.0327***
	(1.95)	(0.01)	(3.20)	(4.72)	(12.50)	(0.84)	(4.16)
Rivals*HHI_Deposits	0.0417***					0.0605**	0.0129
	(3.10)					(2.48)	(0.61)
HHI_Deposits	-1.6747***					-3.6961***	-0.0637
	(-2.65)					(-3.66)	(-0.11)

Note. This table reports Tobit estimates using a cross-sectional data of 2008:Q2 to examine the timing of adoption. The dependent variable is *Time Since Adoption* measured by the number of quarters since adoption as of 2012:Q2. *Local Rivals* are the predicted values using IV approach based on 2012:Q2 data. The marginal effects of key variables are also reported. T-statistics based on heteroskedasticity-robust standard errors clustered by MSA are listed in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 8 The Impact of Mobile App Adoption on Bank Performance (OLS)

	Profitability		Funding	Costs			
Dependent Variable:	ROA	Service Revenue	DEPOSITS	Advertising	Branch Intensity	Worker Per Branch	Labor Cost
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Key Variables:							
POST ADOPT	0.0587	**0.0477*** **	0.1923	**0.0589*** **	0.0265	**0.0027** **	**0.0015*** **
	(1.6231)	**(9.7960)**	(1.0861)	**(4.6769)**	(0.1429)	**(2.1850)**	**(9.5806)**
TIME SINCE ADOPTION	**0.0260** **	**0.0066*** **	0.0685	**0.0137*** **	0.1349	-0.0005	**0.0004*** **
	(2.4175)	**(4.7251)**	(1.0260)	**(2.9113)**	(1.3371)	(-0.8242)	**(9.8621)**
Controls:							
lnassets	0.2931**	0.0624**	1.3886*	0.1910***	-8.0182***	-0.0293***	0.0019**
	(2.4230)	(2.2556)	(1.7562)	(5.5080)	(-5.4961)	(-3.9973)	(2.4302)
Tier1	1.3582	0.0732	-37.3484***	0.9432***	3.9399	0.0924***	0.0117***
	(1.2828)	(0.5751)	(-5.8075)	(4.4514)	(0.5993)	(2.7591)	(2.6138)
Asset Grow	0.4818**	-0.2005***	-2.9290**	-0.0297	-7.6777***	-0.0340***	-0.0067***
	(2.2929)	(-4.4956)	(-2.5147)	(-0.3979)	(-4.8613)	(-3.2628)	(-5.4166)
Local Rivals	0.0002	0.0020***	0.0040	0.0036***	-0.0187***	-0.0002***	0.0001***
	(0.1750)	(11.5973)	(0.7677)	(9.7978)	(-3.8637)	(-4.6917)	(16.7265)
HHI_Deposits	0.7444	0.0097	-3.5702	0.2395	0.5945	-0.0477*	-0.0002
	(1.0047)	(0.1030)	(-0.9927)	(1.3367)	(0.1244)	(-1.8013)	(-0.0875)
ROA		0.8576***	1.0962	1.0901***	-5.9491	-0.0979	0.0221***
		(4.5397)	(0.1421)	(2.6401)	(-0.8463)	(-1.4036)	(3.1826)
Service Revenue	28.0550***		-40.7406	-12.8019***	94.6867	-0.7443**	-0.4436***
	(3.1938)		(-0.9424)	(-4.0663)	(1.5508)	(-2.1703)	(-16.2471)
Core Deposits	0.4020	-0.0356		-0.2234	-4.6581	0.0080	-0.0019
	(0.8302)	(-0.4331)		(-1.3869)	(-1.4396)	(0.3983)	(-0.9360)
Advertising * Dadmk	-0.0870*	-0.0181**	-0.5546**		0.5867**	0.0099***	-0.0003
	(-1.8527)	(-2.2479)	(-2.2375)		(2.2592)	(3.5782)	(-1.3793)
Dadmk	0.0983**	0.0507***	0.1956		-0.2662	-0.0019	0.0019***
	(2.3352)	(6.9175)	(1.2485)		(-1.5300)	(-1.1186)	(9.8427)
Branch Intensity	-0.0068	0.0009	0.0218	0.0014		0.0024***	-0.0000
	(-1.3147)	(1.0632)	(0.9387)	(0.9343)		(4.0739)	(-0.2916)
Worker Per Branch	-1.0190*	0.2816***	4.0831	1.0439***	25.7795***		0.0221***
	(-1.8031)	(4.0438)	(1.4790)	(3.9870)	(6.8694)		(7.9105)
Labor Cost	-14.1784***	-3.7588***	45.1142***	-3.0066***	-56.9942***		
	(-4.0650)	(-10.2836)	(3.0375)	(-2.9312)	(-3.5318)		
CONSTANT	-3.2834**	-0.4681	64.9423***	-2.2614***	119.1859***	0.6161***	-0.0187*
	(-2.0606)	(-1.2505)	(5.9686)	(-4.4876)	(6.0178)	(5.9784)	(-1.7400)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10,868	10,868	10,868	10,868	10,868	10,868	10,868
Adjusted R^2	0.450	0.687	0.868	0.590	0.976	0.948	0.512

Note. This table reports OLS estimates examining the impact of mobile app adoption on the performance of the 694 banks from 2008:Q3 to 2012:Q2, covering 10,868 bank-quarter observations. Performance measures include ROA, deposit-related service fee, deposits relative to assets, advertising expenditures, branch intensity, number of workers to total assets, and labor costs. $POST\ ADOPT_i$ is a dummy variable equal to one once bank *i* adopted a mobile app, and zero otherwise. $TIME\ SINCE\ ADOPTION_i$ is the number of quarters since the adoption for bank *i* in any given quarter. All control variables are lagged by one quarter. Please refer to Appendix B for the variable definitions and sources. The reported t-statistics in parentheses are based on heteroskedasticity-robust standard errors clustered by bank. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.