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Risk and Return of Online Channel Adoption in the Banking Industry *

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Abstract

Online banking has become an important distribution channel for commercial banks. We construct a bank-specific indicator of online channel adoption to study the risk and return of online channels based on a sample of 118 Chinese banks in the period 2002-2016. Our empirical results find that online channel adoption improves the profit efficiency (i.e., positive return) of the adopting banks. Even though cost efficiency deteriorates, such improvement can be attributed to the rise in non-interest income efficiency. In reference to risk management, online channel adoption weakens the loan quality of the adopting banks, which also raises their solvency risk accordingly. Overall, our results suggest that online channel adoption alters the risk-return trade-off of adopting banks. Such risk-return effects are heterogeneous depending on the size, management skill and labour intensity of adopting banks. However, there is no significant return related to the costly content enrichment of online channels. Finally, our results are robust to alternative specifications, alternative sample selection, alternative measures of bank efficiency and risk, alternative estimation methods, and omitted variable biases.

Keywords: Information Technology, Multichannel Retailing, Efficiency, Risk, China

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1. Introduction

Information technology allows producers increasingly to use online channels to distribute and deliver their products. Previous studies find that online channels improve firm performance by reducing cost and increasing output quality (Brynjolfsson and Hitt, 2000), by improving communication and sales with customers (Subramani and Walden, 2001; Lee and Grewal, 2004) and by increasing risk from information technology investment (Dewan and Ren 2007; Dewan et al. 2007). Banks also take advantage of information technology to develop their online distribution channels, which allows them to deliver both traditional services (e.g., opening deposit accounts and transferring funds among different accounts) and new banking services (e.g., electronic bill presentment and payment).[1] Although banks seem to exploit online channels as a source of competitive advantage to improve their performance, evidence of the impact of online channel adoption on bank risk is limited despite risk-return trade-off being an essential part of financial intermediation. Thus, it is imperative to understand how banks can leverage online channels to alter their risk-return relationships.

This paper examines the impact of online channel adoption on risk and return using a sample of 118 Chinese banks over the period 2002-2016. In addition to filling a void in the literature, our empirical analysis of those Chinese banks is motivated by its policy relevance. In 2017, the People's Bank of China released the *13th Five-Year Plan for the Development of Information Technology in China's Financial Sector* to stress the need for the banking industry to adopt information technology. The plan identifies harnessing information technology as a means to drive finance innovation. On the one hand, such policies to promote new technology in commercial banks may affect the performance of adopting banks. On the other hand, policymakers need to be aware that banks may need to adjust their risk management after adopting new technology. Such policy for promoting the use of information technology may alter the trade-off between risk and return in the banking industry. Moreover, financial developments in China have an impact on global financial markets, especially in the case of negative news (Mwase et al. 2016). Further understanding of how financial technology affects the efficiency and risks of Chinese banks has important policy implications.

We conduct the empirical analysis in several steps. First, we collect data from the annual reports of our

[1] For example, a survey reports that 89% of banks increased their investment in channel innovations (PwC's Financial Services Institute, 2015).

sample banks to construct a bank-specific measure of online channel adoption. For a bank, the adoption of online channels is determined by its ability to provide internet banking (i.e., a transactional website), which is the most basic type of online channel. Second, we estimate the profit, cost, interest income, and non-interest income efficiencies of our sample banks using stochastic frontier analysis (SFA) with translog specification. Since these four efficiency measures can be affected by observed and unobserved bank characteristics, we adopt a panel data SFA approach that can control for unobserved heterogeneity. Profit efficiency is an overall measure of bank efficiency, and the other three efficiency measures represent channels through which online channels affect profit efficiency. Importantly, in our work, we define a rise (drop) in those efficiencies as a positive (negative) return after controlling for the variations in outputs, inputs and credit risk of adopting and nonadopting banks. Then, we employ a Z-score (solvency risk) as an overall measure of bank risk and examine the capital adequacy ratio (CAR) and credit risk, measured by the nonperforming loan (NPL) ratio, to explain variations in solvency risk. Third, we estimate how online banking adoption affects bank efficiency and risk. More specifically, we recognize that there may be unobserved factors that affect bank efficiency and risk and, at the same time, contribute to a bank's online channel adoption. The presence of these unobservable common factors tends to cause omitted variables and, hence, endogeneity biases. Thus, we estimate an auxiliary model of online channel adoption, which finds that the adoption of online channels is driven by bank size (in assets and branches), financial resources, bank strategy, competition among banks, and demographics. We then handle the omitted variable bias through modelling the error structure between adoption and efficiency (and between adoption and risk) using the control function approach (Wooldridge 2015).

To anticipate our results, we find that online channel adoption improves the profit efficiency of the adopting banks, which can be attributed to the rise in non-interest income efficiency, even though cost efficiency deteriorates. This finding suggests that online banking adoption promotes new business model development, which increases the efficiency of non-interest income generation through fee-based services. However, the new business model potentially relates to additional marketing, personnel and depreciation expenses. Turning to risk management, online channel adoption weakens the loan quality of the adopting banks, which also raises their solvency risk. Overall, profit efficiency increases as the adopting banks find the rise in non-interest income outweighs the fall in cost efficiency. Since there are joint effects of risk and return from adopting online channels, our results suggest that online channel adoption alters the risk-return trade-off of the adopting banks.

Interestingly, we find several sources of heterogeneity in the effects of online channel adoption on bank efficiency and risk. First, smaller adopting banks enjoy larger positive impacts from online channel adoption, suggesting that smaller banks can utilize online channels to compete with their larger rivals, which have larger physical branch networks. Second, adopting banks with better managerial skills (measured by their idiosyncratic profitability and shareholding of foreign investors) are more capable of realizing cost savings and risk reduction from online channel adoption. Third, the more labour-intensive banks rely more on interest income after the adoption. They maintain a higher capital adequacy, potentially, as a means for a buffer.

In addition, since financial innovation has been developing rapidly in China, we explore how the intensity of online channels (such as mobile and WeChat banking) affects the impact of online channels on bank efficiency and risk. The adopting banks incur a higher cost and experience lower interest income from enriching content in online channels; however, there is no evidence showing that the adopting banks benefit from this approach through, for example, focussing more on hard information-based lending. In addition to showing that the adopting banks do not benefit from focussing more on hard information-based lending than on soft-information-based lending, our results suggest that the content enrichment of online channel adoption becomes a standard competitive tool rather than a competitive edge for the adopting banks.

Finally, we perform several robustness checks. First, we check whether there is a dynamic effect of online channel adoption on the efficiency and risk of adopting banks. Second, we filter the sample with various criteria to check whether our results are robust to the sample selection. Third, we estimate our empirical model with the inclusion of interactive terms among demographic factors. Fourth, we employ alternative outcome measures, such as efficiency rank for efficiency and relative Z-score for solvency risk. Fifth, we estimate our model with the two-stage least square (2SLS) approach. Finally, we perform a placebo test with a placebo measure of online channels that is conducted by randomly assigning online channel adoption to banks. The test checks the extent to which the results are influenced by omitted variables. Encouragingly, our results are mostly robust to those modifications.

Our paper contributes to the literature examining the impacts of online channel adoption on bank performance. The existing literature has inconclusive evidence on the effects of online channel adoption on bank performance. Although earlier studies, such as Egland et al. (1998), Sullivan (2000) and Furst et al. (2002), do not find that internet banking improves bank performance, recent studies show positive effects of internet banking on bank performance.[2] Hernando and Nieto (2007) find that internet banking improves profitability through increased reduction of overhead expenses of Spanish banks in Spain. Onay and Ozsoz (2013) find that internet banking deteriorates profitability through decreasing the interest income of Turkish banks, even though non-interest income increases after internet banking adoption. In a closer relationship with our work, two existing works shed a light on both performance and risk from adopting online channels. DeYoung et al. (2007) investigate U.S. community banks and find that internet banking improves profitability through increasing non-interest income. Additionally, adopting banks focus more on hard information-based lending, such as credit card loans, over soft information-based lending. Ciciretti et al. (2009) find that internet banking raises bank returns and reduces credit risk and the volatility of stock returns in Italy.

Our work differs from previous studies in four aspects. First, we provide new evidence on the heterogeneities of how online channel adoption affects bank efficiency and risk. We find that the size, management skill and labour intensity of adopting banks affect their risk-return trade-offs from using online channels. Second, we construct an intensity measure of online channel adoption that counts the content provided in online channels. Specifically, this measure takes the value of one if banks provide a transactional website as their only online channel, the value of two if banks allow the use of mobile devices to access online channels, and the value of three if banks further add the function of WeChat banking to their online channels. Third, we examine a larger set of risk measures, including solvency and credit risks. Thus, we are able to provide a more comprehensive analysis of the joint effects of risk and return from adopting online channels in the banking industry. Fourth, we are the first to provide an empirical analysis of how online channel adoption affects bank efficiency and risk in China.

The rest of this paper proceeds as follows. Section 2 provides a theoretical framework to understand how online channel adoption affects bank efficiency and risk. Section 3 introduces the institutional background. Section 4 describes the data and empirical methodology. Section 5 presents the empirical

[2] All of the following four papers use financial ratios rather than efficiency measures.

results along with various robustness checks. Section 6 concludes.

2. Theoretical Framework and Literature

This section first discusses how online channel adoption affects bank profit, in particular through cutting cost and enhancing interest and non-interest incomes. The net effects of online channel adoption on profit are expected to be positive because the adopting banks would not adopt online channels if they did not benefit from doing so. However, the responses of cost and incomes to online channel adoption are expected to be mixed.

First, the effects of online channel adoption on cost are expected to be ambiguous. On the one hand, online transactions cost much less than do those at branches, which reduces overhead expenses and their associated costs (Hernando and Nieto, 2007). On the other hand, online channel adoption requires a higher fixed infrastructure cost, which may be spread out as overhead over the years after adoption. As DeYoung and Duffy (2004) state, offering online services is not only a technological but also a marketing feat. A large amount of advertising expenditures is needed for banks to ensure that their online services are noticed. Online channel adoption also requires skilled IT workers to maintain the services, which increases personnel expenses (DeYoung et al., 2007).

Second, the effects of online channel adoption on income are expected to be ambiguous. On the one hand, online channel adoption facilitates lending based on hard information, which may increase credit card loans (DeYoung et al., 2007), auto loans, and mortgages. On the other hand, online channel adoption may reduce lending based on soft information, such as loans to small to medium-sized enterprises (SMEs). The impact of online channel interest income depends on the strength of these two forces. Turning to non-interest income, adopting banks can charge fees for online services. Adopting banks can generate fee income from various services provided online, such as loan origination and service fees and online brokerage fees. Indeed, previous studies find that online channel adoption increases non-interest income (DeYoung et al., 2007, Hernando and Nieto, 2007, Ciciretti et al., 2009, Onay and Ozsoz 2013).[3] We expect that online banking adoption increases non-interest income

[3] Although the cost-reducing effect from adopting online channels may reduce the interest rates charged on loans, raise the interest rates paid on deposits and reduce the fees charged for services, we expect those cost-reducing effects are captured by the input prices used in SFA for estimating efficiencies.

efficiency.

Further, online channel adoption affects bank strategy, which affects not only bank efficiency but also bank risk. We take solvency risk as the overall measure of bank risk because it informs the soundness of banks. The net effect of online channel adoption on solvency risk is expected to be ambiguous, depending on the responses of credit risk and capital adequacy to online channel adoption.

For credit risk, online channel adoption facilitates lending based on hard information, such as credit card loans, auto loans, and mortgages, but reduce lending based on soft information such as loans to SMEs. As a result, their use may increase or decrease the credit risk of adopting banks (DeYoung et al., 2007; Ciciretti et al. 2009). Further, the services provided through online channel adoption may affect the adopting banks' decisions on capital adequacy. For example, less reliance on interest income may encourage lower capital for risk management purposes. Additionally, a change in credit risk driven by online channel adoption may also induce banks to adjust their capital adequacy by affecting their nonperforming loans, capital cost demanded by investors, and precautionary motives (Berger and DeYoung, 1997). Thus, we expect mixed impacts of online channel adoption on capital adequacy and credit risk, which in turn produce ambiguous impacts of online channel adoption on solvency risk.

In summary, online channel adoption is expected to have a positive effect on profit efficiency, which is partly driven by a rise in non-interest income efficiency. Nonetheless, in response to online banking adoption, there are mixed responses in cost and interest income efficiencies. Further, online channel adoption is expected to have an ambiguous effect on solvency risk because, in response to online banking adoption, there are mixed responses in capital adequacy and credit risk.

3. Institutional Background

Online channel adoption is becoming an important business model for most Chinese banks. China Merchants Bank was the first to adopt an internet banking service in 1997, after which internet banking spread rapidly throughout the Chinese banking industry. Internet banking provides 24-hour banking services for bank customers. Their customers can login to the online channel to check their account balances and transaction details, transfer money, pay phone and other bills, and buy investment products. Customers can also apply for personal consumption loans, such as loans for education and for housing, through the online channel.

Since the Bank of China began to extend online channels to mobile devices in 1999, an increasing number of banks have followed their lead, allowing consumers to check their bank accounts, perform transactions, and transfer funds with their mobile devices. Nonetheless, mobile banking did not develop rapidly until 2011. By 2017, the amount of banking transactions performed through mobile devices increased to RMB 21.6 billion, a growth rate of 53.7%.[4] In addition, an increasing number of banks started to include WeChat banking as an added function of online channels to attract more consumers. WeChat banking is a new service based on WeChat, a messaging and social media app developed by Tencent. WeChat banking is different from WeChat pay, Alipay and Unionpay, which are just payment systems connected with bank accounts.[5] Rather than using online channels from different banks, consumers can manage accounts and receive transaction notifications from different banks in WeChat if those banks deploy WeChat functions in their online channels. China Merchant Bank was the first to launch WeChat banking in 2013, after which banks increasingly began to offer WeChat banking services.

Although online channel adoption in China emerged later than in other developed countries, it experienced rapid development in China's banking industry. Transaction amounts via online channels achieved a volume of RMB 1570.9 trillion in 2016, with an average annual growth rate of 34% from 2002 to 2016. Currently, all major banks and most small and medium-sized banks offer online channels. Figure 1 shows the number of banks that adopted online channels by year. Before 2007, only 30 banks had adopted internet banking, a number that includes 4 state-owned commercial banks (SCBs), 12 joint-stock banks (JSBs), 12 city commercial banks (CCBs) and 3 rural commercial banks (RCBs). Since 2007, an increasing number of banks have deployed online channels. By the year 2016, there were 125 banks providing online channel services (4 SCBs, 13 JCBs, 84 CCBs, and 24 RCBs).

[Insert Figure 1 here]

The diffusion of online channel adoption in China shares some similarities with that in other countries.

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[4] For example, the number of mobile payments in China is 11 times that in the United States (McKinsey Global Institute, 2017).

[5] See an introduction to Wechat banking of Industrial and Commercial Bank of China (ICBC). http://www.icbc.com.cn/ICBC/E-banking/PersonalEbankingService/BankingHome/WeChatBanking/

First, larger banks, namely SCBs and JSBs, adopted online channels earlier than did smaller banks, namely CCBs and RCBs (see Figure 1). Second, the number of bank accounts of retail consumers is larger than that of business consumers. The number of accounts using retail online channels was 365 million in 2016, with a growth rate of 8.7%, while that of business consumers only grew by 1.9%. (CNNIC, 2017; CFCA, 2017). Third, the development of online channels is more rapid in areas with younger and more-educated populations because they have a stronger habit of purchasing online (Yuan et al., 2010).

4. Data and Empirical Methodology

In this section, we first describe the dataset used in this paper, followed by the empirical model for analysing the effects of online channel adoption on bank efficiency and risk. Finally, we discuss in detail the construction of the dependent variables and the main explanatory variables.

4.1 Data

We compile an unbalanced panel dataset containing data for 118 Chinese banks over the period 2002-2016 that includes 4 SCBs, 13 JSBs, 75 CCBs and 26 RCBs. Financial data are mainly collected from Bankscope for the years 2014 and before, and the data for the remaining two years are collected manually from the banks' annual reports. The unique feature of our dataset is that our bank-specific variable measuring the adoption of online channels is hand-collected. The data on availability of online channels are drawn from annual reports released by our sample Chinese banks. Table 1 reports the distribution of observations. In the early years, few banks published sufficient information for estimating bank efficiency. Further, some smaller banks do not provide their annual reports as completely as do publicly listed banks (especially for earlier years). Hence, the observations decrease for the second-to-last sample year, as the data for the last two years are manually collected.

[Insert Table 1]

Our bank-year sample size is 703. The sample size is limited by the data availability for estimating the empirical model introduced in the next subsection. Nonetheless, our sample is still representative for the Chinese banking industry, covering approximately 90% of the banking assets in China in 2015, even though the percentage has been decreasing over time. Further, our data sources on financial data are consistent with the existing literature (Berger et al., 2009; Jiang et al., 2009; Berger et al., 2010;

Sun et al., 2013; Jiang et al., 2013; Cheng et al., 2016; Zhu and Yang, 2016).

4.2 Empirical Model

To analyse the effects of online channel adoption on bank efficiency and risk, we specify the following empirical model:

$$Efficency_{it} \ \ (or \ \ Risk_{it}) = \alpha_0 ONLINE_{it} + X_{it}\beta + \eta_t + \eta_b + \eta_b \times t + \varepsilon_{it}, \tag{1}$$

for bank *i* in year *t*. *Efficiency* is the measurement of bank efficiency, which will be described in detail in subsection 4.3. *Risk* is the measurement of bank risk, which will be described in detail in subsection 4.4. Our variable of interest is *ONLINE*. It is a measure of adoption of online channels and takes the value of one after our sample bank adopts online channels and zero otherwise.

X is a vector of control variables. We include three bank characteristics varying at the bank-year level that may affect bank efficiency and risk. We control for bank size by including the total assets (*SIZE*) and total number of branches normalized by total assets (*BRANCH*). A larger bank may enjoy a higher efficiency and lower risk by exploiting better diversification in loan portfolios and a larger product scope offered to consumers (Hughes and Mester 2010). We also control for geographical diversification by including the number of cities in which a bank has branches (*NCITY*). Previous studies suggest that there are mixed effects of geographic diversification on bank performance. On the one hand, geographic diversification increases agency cost by making it more difficult to monitor the manager (Bandelj, 2016). On the other hand, geographical diversification allows banks to diversify their risk over different geographic locations.

Further, we include a set of economic and demographic variables. First, we include the Herfindahl-Hirschman Index (*HHI*) measured by the number of branches operated by all banks in their main operating city to measure the effects of competition on bank efficiency and risk (DeYoung, 2007; Hernandez-Murillo et al., 2010). Second, we include per capita income (*PINC*), population (*POP*), and number of firms (*NFIRM*) in their main operating city to control for the effects of economic development on bank efficiency and risk. Further, we include year fixed effects η_t and bank-type fixed effects η_b to capture unobserved heterogeneities across banks and years. The bank-type specific trend $\eta_b \times t$ captures the differentiated trends in efficiency and risk across bank types. The bank-type fixed effects and specific trends are potentially driven by the differences in regulatory measures across bank types. Standard errors are clustered at the bank-type level to allow for serial correlation in error terms and correlation in error terms across banks of the same type.

4.2.1 Addressing Potential Endogeneity of Online Channel Adoption

Although we take unobserved bank heterogeneity into account to estimate bank efficiency and risk, there are potential unobserved factors that drive an adoption of online channels and bank efficiency and risk. For example, an unobserved managerial ability may attempt to raise the efficiency of inefficient banks by adopting online channels, driving a negative correlation between *ONLINE* and the error term in Equation (1).

We use a control function approach to control for this potential endogeneity (Wooldridge, 2015). An advantage of this approach is that it can be more efficient than a standard 2SLS approach. However, a requirement of this approach is the assumption that one has modelled correctly the conditional mean of the error term. Rather than relying on a few instrumental variables (IV) in the 2SLS approach, we need an elaborated specification for online channel adoption. Thus, following the literature of online channel adoption, we specify the reduced-form Probit model for adoption of online channels as follows:

$$ONLINE_{it} = 1[X_{it-1}\theta_1 + Z_{it-1}\theta_2 + \nu_t + \nu_b + \nu_b \times t + \mu_{it}] \qquad (2)$$

Equation (2) includes the set of variables used in Equation (1), namely the vector *X*, year fixed effects, bank-type fixed effects, and bank-type specific trends. More importantly, it also includes a set of instrumental variables (IV) *Z* that drives the adoption of online channels suggested in the literature. To ensure the explanatory variables in this equation are exogenous, we lag both the vectors *X* and *Z* for one year. Since Equation (2) is not the focus of our analysis, for the sake of brevity, we discuss its details in the first stage in Appendix 2. Overall, we find that there are five sets of variables included in *Z* that explain online channel adoption: size, financial performance, business strategy (such as loan/asset ratio, non-interest income ratio and business/customer loan ratio), competition, and demographics.[6]

[6] The pattern of online channel adoption among our sample banks is consistent with those reported in the literature (Egland et al.,1998, Courchane et al., 2002, Corricher 2006, DeYoung et al., 2007, Hernando and Nieto 2007, Ciciretti et al., 2009, Hernandez-Mutillo et al., 2010, Onay and Ozsoz 2013, Pana et al., 2015, Dandapani et al., 2016; He et al. 2019).

Under the assumption that $\{\varepsilon_{it}, \mu_{it}\}$ are jointly normally distributed, we derive the following relationship:

$$E(\varepsilon_{it}|ONLINE_{it}, X_{it}) = E(\varepsilon_{it}|\mu_{it}, X_{it}, Z_{it}) = E(\varepsilon_{it}|\mu_{it}) = \gamma GR_{it} \quad (3)$$

The first equality in Equation (3) follows from the reduced-form models for online channel adoption in Equation (2). The second equality in Equation (3) follows from the observables $\{X_{it}, Z_{it}\}$, which are independent of the unobservable ε_{it}. Equation (3) suggests that we can include the variable GR_{it} to control the potential endogeneity of online channel adoption in Equation (1). The variable GR_{it} is defined as $\left(ONLINE_{it} \times \frac{\phi(U_{it})}{\Phi(U_{it})} + (1 - ONLINE_{it}) \times \frac{-\phi(U_{it})}{1-\Phi(U_{it})}\right)$, where $U_{it} = \widehat{ONLINE} / \sigma_\mu$ is the generalized residual from Equation (2). The functions $\varphi(.)$ and $\Phi(.)$ are the pdf and cdf of a standard normal distribution. The variable σ_μ is the standard deviation of μ_{it}, which is used as the normalization for the first-stage Probit estimation of Equation (2).

Equations (1)-(3) suggest the following estimation procedure. First, we estimate Equation (2) to obtain the generalized residual GR_{it}. Then, we estimate the following empirical model:

$$Efficency_{it} \ (or \ Risk_{it}) = \alpha_0 ONLINE_{it} + X_{it}\beta + \gamma GR_{it} + \eta_t + \eta_b + \eta_b \times t + e_{it}, \quad (4)$$

The idea behind the control function approach is that it adds the generalized residual as a covariate to turn the endogenous variables appropriately exogenous in a second-stage estimating equation, Equation (4). Intuitively, the variable GR_{it} works similarly to the inverse Mill's ratio in the sample selection model.

Finally, we conclude this subsection by identifying several advantages of using this approach. First, it is simple to estimate since a least-squares fitting of Equation (4) will produce a consistent estimate of α_1. Second, Wooldridge (2015) indicates that the coefficient γ serves as a heterogeneity-robust Hausman test for the null hypothesis that $ONLINE_{it}$ is exogenous. Further, the coefficient $\gamma = Cov(\varepsilon_{it}, \mu_{it})/Var(\mu_{it})$; a positive (negative) γ indicates that more efficient and riskier banks are more (less) likely to adopt online banking. Third, this approach is more efficient compared to including the interaction of our instrument with the additional variable as a second instrument in the 2SLS setting. This feature facilitates incorporating additional interaction terms to analyse the dynamic and heterogeneous effects of online channel adoption (see Sections 5.2-5.3).

4.3 Bank Efficiency

We employ parametric SFA to estimate bank efficiency and assess whether a bank responds to relative prices in choosing its inputs and outputs to maximize profits or minimize costs (Hughes and Mester, 2010). We use the notion of profit efficiency – a bank's profits relative to the observed most profitable bank, controlling for output and input conditions – to measure a bank's overall performance level (Berger and Mester, 1997). We then estimate cost efficiency, interest income efficiency, and non-interest income efficiency to explore the channel through which online channel adoption affects profit efficiency.[7]

The four-error component stochastic frontier model proposed by Kumbhakar et al. (2014) and Tsionas and Kumbhakar (2014) is used to estimate four efficiency measures. This method has the advantage of allowing for random bank effects and disentangling persistent inefficiency from time-varying inefficiency.[8] The time-varying, rather than time-invariant, bank profit efficiency is used to assess the implications of online channel adoption on overall efficiency. The efficiency measure assumes a value between zero and one (or 100%), with one implying the highest level of efficiency and zero implying the lowest level. The estimated procedure and parameter estimates of SFA are reported in Appendix 3.

The average profit efficiency, cost efficiency, interest income efficiency, and non-interest income efficiencies are 79%, 94%, 82%, and 65%, respectively (see Table 2). The cost and interest income efficiencies yield the larger average values, while the non-interest income efficiency yields the smallest value. The relative magnitudes of these measures are similar to those reported in Berger et al. (2009) and Jiang et al. (2013), even though the estimation technique adopted here is different from those in these studies.[9]

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[7] The use of SFA facilitates the comparison of our results with those of previous studies, such as Berger et al. (2009), Berger et al. (2010), Jiang et al. (2013), and Sun et al. (2013).

[8] Tsionas and Kumbhakar (2014) find that this model outperforms a simpler model without bank fixed effects or permanent inefficiency in analysing the efficiency of US banks.

[9] Our estimates of average profit, cost, non-interest income, and interest income (time-invariant plus time-varying) efficiencies are 58%, 86%, 83%, and 65%, respectively, and are closer to efficiencies reported in previous studies. For example, Berger et al. (2009) report the mean scores are 47.6% for profit efficiency and 89.7% for cost efficiency. Detailed

[Insert Table 2]

4.4 Bank Risks

Our empirical analysis includes several measures of bank risk that are commonly used in the existing literature. The Z-score is a measure that assesses overall solvency at the bank level (Demirguc-Kunt and Huizinga, 2010; Cheng et al., 2016), where *Z-score* = (ROA+CAR)/sd(ROA) as the proxy variable of bank solvency, ROA is the rate of return on average assets, CAR is the capital adequacy ratio, and sd(ROA) is the standard deviation of ROA over the sample period. We choose *Z-score* as an overall measure of bank risk because a higher (lower) *Z-score* value indicates less (more) overall bank risk exposure and a higher (lower) bank solvency.

Consistent with the BASEL III framework, we also examine the CAR (Cheng et al., 2016; Zhu and Yang, 2016) to measure the extent to which a bank can absorb potential losses. The CAR also informs whether the variation in *Z-score* is driven by capital risk. In addition, we examine the credit risk driven by online channel adoption on the asset side. We use the NPL ratio (Ciciretti et al., 2009; Zhu and Yang, 2016) to measure credit risk. The variable *NPL* is defined as nonperforming loans over total loans.

Table 2 reports the descriptive statistics of our risk measures. On average, the *Z-Score* is 38.4, which indicates that the ROA and CAR can handle an ROA shock as large as 38 times its standard deviation. Our sample banks have capital at 13% of total assets and less than 2% of NPL over total loans, on average.

4.5 Online Channel Adoption

We measure the adoption of online channels with a dummy variable that takes a value of one for a bank adopting online channels (*ONLINE*), and zero otherwise. When a bank adopts online channels, it can provide basic online channel services including the following: 1) account inquiry and maintenance, 2) fund transfer and remittance, 3) automatic bill and credit card payments, 4) savings

results are available upon request.

and investment transactions, 5) retail and commercial banking transactions, and 6) online trading.[10]

The upper panel of Figure 2 shows the portion of our sample banks with online channels. The number of banks with online channels increased slightly at the beginning of the sample period, but the number has grown rapidly since 2007. The portion of banks that adopted online channels jumps from 21% in 2007 to 96% in 2016. Table 2 reports that 87% of our observations have *ONLINE* = 1.

[Insert Figure 2]

The right panel of Table 2 reports the descriptive statistics between the nonadopting and adopting banks. Overall, the adopting banks have higher efficiency and risk than the nonadopting banks. However, those differences are mostly insignificant and can be driven by confounding factors. Thus, we now turn to the results from our empirical model, which controls for bank heterogeneity and selection into adoption.

5. Empirical Results

This section first covers the benchmark results for the effects of online channel adoption on bank efficiency and risk, along with several robustness checks. Then, we explore the heterogeneous effects of online channel adoption on bank efficiency and risk.

5.1 Baseline Results

This subsection discusses the effects of *ONLINE* on bank efficiency and risk in Table 3. We start with the baseline results reported in Panel A. The coefficients of *GR* are significantly negative in Columns 1 and 4, and is significantly positive in Column 5, which suggest that there are omitted factors driving inefficient and solvent banks to adopt online channels. These results also justify the use of control function approach.[11]

[10] For example, on the website for the Industrial and Commercial Bank of China (ICBC), personal internet banking is described as "an internet banking channel that provides ICBC personal clients with online financial services, including account inquiry, transfer and remittance, investment and financing, and online payment", and corporate internet banking is "the corporate electronic financial accounting management system developed by ICBC." Through corporate internet banking, "the insurance company HQ may exercise financial control over the subsidiaries. It renders real-time inquiries over the branch companies' account balance, batch fund collection, batch fund payment, and outward account payment."

[11] The results from OLS estimation are available upon request.

Column 4 report that the coefficients of *ONLINE* are statistically positive in the non-interest income efficiency model. Online channel adoption increases the non-interest income efficiency of adopting banks. Further, although the coefficient of *ONLINE* is marginally insignificant at 10%, evidence in the latter parts of our paper (see Table 4) shows that there is an overall positive impact of online channel adoption on the profit efficiency of adopting banks. The magnitude of the coefficients shows that this effect is also economically significant. If a bank's probability of online channel adoption increases one standard deviation, its profit and non-interest income efficiencies will increase by 0.16 and 0.27 of their standard deviations, respectively.[12] However, the impact of online channel adoption on cost and interest income efficiencies is insignificant.

[Insert Table 3 here]

Columns 5-7 report the relationship between online channel adoption and bank risks. The coefficients of *ONLINE* are significantly negative and positive in Columns 5 and 7, respectively. However, the coefficient of *ONLINE* is insignificant in Column 6. Online channel adoption raises credit and solvency risks. If a bank's probability of online channel adoption increases one standard deviation, its *Z-Score* and *NPL* will decrease by 0.23 and increase by 0.23 of their standard deviations, respectively.

Now, we explore the variations identifying the baseline results. Table 1 reports the distribution of those three types of adopter in each sample year. There are three types of banks in our sample: early adopters (banks that adopted online channels in or before the first year of sample observations), recent adopters (banks that adopted online channels after the first year of observations), and nonadopters (banks not adopting online channels until the last year of observations). Thus, there are two sources of variation to identify the parameter α_0 in Equation (4) through difference-in-differences (DiD).

First, the DiD estimate can be identified by comparing the outcome variables of recent adopters and late adopters (nonadopters and recent adopters adopting online channels in later years). Recent adopters and late adopters are used as the treatment and control groups, respectively. We estimate Equation (4) with a subsample of recent adopters and late adopters and report the results in Panel B of

[12] A standard deviation of adoption probability is 0.20.

Table 3. Adopting online channels has a strong impact on recent adopters relative to late adopters. Generally, the coefficients in *ONLINE* are more significant than are those reported in Panel A, Table 3. Thus, this subsample is a driving force behind our baseline results reported in Panel A, Table 3.

Second, the DiD estimate can be identified by comparing the outcome variables of recent and early adopters. We estimate Equation (4) with a subsample of recent and early adopters and report the results in Panel C of Table 3. Generally, the coefficients in *ONLINE* are smaller in magnitude and less significant than are those reported in Panel B, Table 3. Adopting online channels has a weaker impact on recent adopters in this case because those early adopters (i.e., the control group) often grow faster than late adopters do (i.e., the control group in the previous case), especially in their efficiencies. Thus, in contrast to the previous subsample, this subsample drives our baseline results reported in Panel A, Table 3 in a more conservative direction.

5.1.1 Discussion

Our results on bank efficiency are consistent with the empirical prediction of our theoretical framework in the following aspects. Online channel adoption improves the profit efficiency of the adopting banks, which can be attributed to a rise in non-interest income efficiency. The improvement suggests that online banking adoption promotes new development of a business model, which increases the efficiency of generating non-interest income through fee-based services (for example, loan origination or commitment). Further, the insignificant effect on interest income efficiency may relate to several factors: 1) the information effect of online channel adoption on interest rate setting is insignificant in our setting; 2) the beneficial effect is offset by the stronger competition among adopting banks; or 3) there is a cross-subsidization between interest income and non-interest income. As a result, the rise in non-interest income after adopting online channels alleviates the upward interest rate pressure.

Our results on the positive effect of online channel adoption on profit efficiency are consistent with previous studies based on samples from Italy (Ciciretti et al., 2009), Spain (Hernando and Nieto, 2007), the United States (DeYoung et al., 2007; Pana et al., 2015), and Turkey (Onay and Ozsoz, 2013). The non-interest income channel to increase profitability is consistent with DeYoung et al. (2007), Ciciretti et al. (2009) and Onay and Ozsoz (2013), who find that internet banking increases profitability through raising non-interest income.

Our results on bank risk elaborate on the mixed responses of bank risk to online channel adoption indicated in the empirical prediction of our theoretical framework. First, Column 7 reports that online channel adoption raises credit risk, suggesting that, after the adoption of online channels, banks suffer from switching to hard information-based lending. Second, the adoption of online channels can be a driver of higher solvency risk, which potentially relate to two factors: 1) the (insignificant) reduction of a capital buffer. Such bank behaviour is consistent with the adjustment of capital buffers when the cost of capital is altered by its higher credit risk (Jokipii and Milne, 2011); and 2) the rise in return volatility, in contrast to Ciciretti et al. (2009), driven by a higher credit risk. Overall, our results suggest that there are joint effects of risk and return from adopting online channels.

Finally, the signs on control variables are reasonable. The coefficients of ln(*SIZE*) are significantly positive in Columns 1 and 5, which shows that larger banks are more profitable and solvent than are small banks. The coefficients of *BRANCH* are significantly positive in profit, interest income and non-interest income efficiency models but are negative in the cost efficiency model. The results indicate that banks with more branches generate higher interest and non-interest incomes but incur a higher cost. In addition, the coefficients of ln(*NCITY*) are significantly negative in Column 1. Geographically diversified banks have lower efficiencies, which is consistent with Berger et al. (2010). The coefficient of *HHI* is positive in Column 5 but negative in Column 7. Banks with market power are more solvent and have lower credit risk, which is consistent with the "quiet life" hypothesis (Hicks 1935). We do not interpret the three demographic variables because they are correlated with each other and only serve as control variables for economic development.

5.2 Robustness Checks

5.2.1 Dynamics

Online channel adoption may have a gradual influence on bank efficiency and risk, which manifests different impacts in the short and long term. For example, Hernando and Nieto (2007) find that online channel adoption reduces overhead expenses 1.5 years after the adoption. To investigate the dynamic effects of online channel adoption, we estimate empirical models that capture both short- and long-term effects of online channel adoption on bank efficiency and risk. The specification is as follows:

$$Efficency_{it} \ \ (or \ \ Risk_{it}) = \alpha_0 ONLINE_{it} + \alpha_1(ONLINE_{it-1} + ONLINE_{it-2})$$
$$+\alpha_2(ONLINE_{it-3} + ONLINE_{it-4}) + \alpha_3 ONLINE_{it-5+}$$
$$+X_{it}\beta + \gamma GR_{it} + \eta_t + \eta_b + \eta_b \times t + e_{it} \qquad (5)$$

The variable $ONLINE_{it-1} = 1$ for the first year after the adoption of online channels, and zero otherwise. The variables $ONLINE_{it-2}$, $ONLINE_{it-3}$ and $ONLINE_{it-4}$ are defined analogously. The variable $ONLINE_{it-5+} = 1$ for the fifth year and onwards after the adoption of online channels. The coefficient α_0 characterizes the effects of online channel adoption on bank efficiency and risk in the year of adoption. The coefficient $\alpha_0+\alpha_1$ ($\alpha_0+\alpha_2$) characterizes the effects of online channel adoption on bank efficiency and risk in the *1*st and *2nd* (*3rd* and *4th*) years after the adoption. The coefficient $\alpha_0+\alpha_3$ characterizes the long-term effect of online channel adoption on bank efficiency and risk in the 5th year and onwards after the adoption of online channels.

Panel A of Table 4 reports the results of Equation (5). The positive effect of online channel adoption on profit (cost) efficiency emerges in 1-2 years (3-4 years) after the adoption, which suggests that it may take a few years to start restructuring after adopting online channels. In particular, the new business model, including the services provided through online channel adoption, potentially relates to the additional marketing, personnel and depreciation expenses in the longer term. This increased cost effect of online channel adoption is consistent with DeYoung and Duffy (2004) and DeYoung et al. (2007). Nonetheless, the responses of non-interest income efficiency, *Z-score* and *NPL* do not appear in delay.

Importantly, the long-term effects ($\alpha_0+\alpha_3$) are consistent with the coefficients of *ONLINE* reported in Panel A, Table 3. Thus, given that most of the outcome variables do not exhibit long delays in response to online banking adoption, we focus on the empirical model without dynamic effects in this paper.

[Insert Table 4 here]

5.2.2 Sample Selection

Since there is an increasing number of banks in our sample over time, we perform a robustness check on whether the sampling of our banks introduces any significant bias in our main results. Intuitively, the inclusion of a bank in BANKSCOPE does not relate to its efficiency and risk, so the bias from sample selection would not be substantial. To verify our intuition, we estimate Equation (4) with banks staying in the sample for at least three years and report the results in Panel B of Table 4.[13] Encouragingly, the coefficients of *ONLINE* have signs consistent with our baseline results.

5.2.3 Additional Control Variables

In this subsection, we conduct a robustness test for our baseline results by including additional control variables. Specifically, we include the three interaction terms of *PINC*, *POP* and *NFIRM* as control variables. Panel C of Table 4 reports the corresponding results, which are consistent with our baseline results.

5.2.4 Alternative Measures of Bank Efficiency and Risk

In this subsection, we first use the efficiency ranks based on an ordering of the bank's efficiency levels in each year as the dependent variables (Berger et al., 2009). The ranks are converted to a uniform scale over [0,1] using the formula $(Order_{it} -1)/(n_t -1)$, where $Order_{it}$ is the place in ascending order of bank i in year t in terms of its efficiency level, and n_t is the number of banks in year t. Thus, bank i's efficiency rank in year t yields the proportion of the other sample banks with lower efficiency levels. The bank with the lowest efficiency level has the worst rank of 0, and the bank with the highest efficiency level has the best rank of 1.

Although efficiency levels are more accurate than ranks because the levels account for the measured distance from the best-practice frontier, efficiency ranks have the benefit of being more comparable over time. Efficiency ranks for every period follow the same uniform [0,1] distribution, whereas the distribution of efficiency levels may differ with the macroeconomic environment over time. We estimate Equation (4) using the efficiency rank as the dependent variable and report the results in Panel D of Table 4. The coefficients of *ONLINE* have consistent signs with our baseline results.

Second, we use alternative variables as dependent variables to measure a bank's risk each year. Fang et al. (2014) argue that it is useful to measure the relative solvency (i.e., how close individual banks are to the most solvent among them). They argue that the same Z-scores may be associated with banks'

[13] The results for the samples with banks staying for at least four and five years are available upon request.

different deviations from their potentially highest levels of solvency given their output and input mixes. In practice, we employ an SFA to fit an upper envelop of Z-scores. The difference of the actual Z-score from the implicit optimal value represents the deviation of a bank's solvency from its potential highest solvency.[14] We report the results in Panel D of Table 4 under Column 5 (Z-Score). The result is consistent with our baseline results.

5.2.5 IV Estimation

This subsection performs a robustness check with another estimation method to handle the potential endogeneity of *ONLINE*. Specifically, we employ the 2SLS approach for the following estimating equation:

$$Efficency_{it}\ \ (or\ \ Risk_{it}) = \alpha_0 + \alpha_1 \widehat{ONLINE}_{it} + X_{it}\beta + \eta_t + \eta_b + \eta_b \times t + \varepsilon_{it}, \qquad (6)$$

To estimate the above equation, we replace $ONLINE$ with its fitted probabilities, $\widehat{ONLINE}$. In the first stage, we employ Business/Consumer Loan as our IV, i.e., Z_{it} = {MMC_{it}, *Business/Consumer Loan*$_{it}$}. Note that the IV estimation has a robustness property; the model for P($ONLINE_{it}$ = 1|X_{it}, Z_{it}) does not have to be correctly specified. Thus, the set of variables Z_{it} in the IV estimation can be much smaller than that used in the control function approach.

Panel E of Table 4 reports the results of Equation (6). The coefficients of $\widehat{ONLINE}$ in Columns 1-4 have signs consistent with those in Table 2. However, Column 7 has significant but opposite signs compared with those in Table 3. Although the null hypotheses of over- and under-identification tests are rejected, that of a weak identification test cannot be rejected.[15] We prefer the use of a control function to the 2SLS approach in our context and interprets that most of our coefficients are robust to the use of an alternative estimation method.

5.2.6 A Placebo Test

In this subsection, we check the extent to which the results are influenced by any other omitted variables. A placebo test is conducted by randomly assigning the adoption of online channels to our

[14] We follow the procedure outlined in Appendix 3 to estimate Z-Score efficiency. Nonetheless, we employ the overall technical efficiency in this case because there is too little variation on the time-varying component.

[15] The coefficient of *Business/Consumer Loan* is significantly negative, while that of *MMC* is insignificant in the first stage estimation.

sample banks. Given the random data generating process, the *PLACEBO-ONLINE* variable should have no significant estimate with a magnitude close to zero. A different result would indicate a misspecification of our empirical model.

[Insert Figure 3 here]

We estimate Equation (4) with the *PLACEBO-ONLINE* variable. To increase the identification power of the placebo test, we repeat the regression 250 times. Figure 3 shows the distribution of coefficients of *PLACEBO-ONLINE* for all four efficiency measures and four risk measures. The distribution of coefficients of *PLACEBO-ONLINE* is clearly centred around zero. Further, the null hypothesis that the median (or mean) of coefficients of *PLACEBO-ONLINE* is zero cannot be rejected for all efficiency and risk measures, suggesting that there is no effect with the *PLACEBO-ONLINE* variable.

5.3 Heterogeneities

In this section, we explore several heterogeneities in how online channel adoption affects bank efficiency and risk. Exploring such heterogeneities has important managerial implications because doing so allows bank management to know the extent to which their banks will benefit from online channel adoption. To do so, we develop a specification to explore the heterogeneous effects of online channel adoption on bank efficiency and risk as follows:

$$\begin{aligned} Efficency_{it}\ \ (or\ \ Risk_{it}) = \alpha_0 + \alpha_1 ONLINE_{it} + \alpha_2 ONLINE_{it} \times SOURCE_{it} \\ + X_{it}\beta + \gamma GR_{it} + \eta_b + \eta_t + \eta_b \times t + e_{it} \end{aligned} \tag{7}$$

Equation (7) also includes the vector of control variables *X*, bank-type fixed effects, year fixed effects, bank-type-specific trend and a control function. The coefficient of interest is α_2, which indicates how the variable $SOURCE_{it}$ affects the impacts of online channel adoption on bank efficiency and risk.

5.3.1 Size

Banks are heterogeneous in size. Specifically, there are four types of banks in our sample, namely, SCB, JSB, CCB and RCB. We set SOURCE = *1{CCB or RCB}*, which is an indicator for CCBs and RCBs, which are smaller than the other two types of banks. Panel A of Table 5 reports the results of Equation (7), where the coefficients of *ONLINE X 1{CCB or RCB}* are significant in Columns 1-4.

Online channel adoption provides a higher return (in profit through a higher interest and non-interest incomes) but incurs a higher cost for smaller banks. This finding suggests that the smaller banks utilize online channel adoption to improve their lending and develop new business models in the face of their larger rivals, which often have a larger physical branch network. At the same time, smaller banks incur a relatively higher cost for restructuring.

[Insert Table 5 here]

5.3.2 Managerial Skill

First, we set SOURCE = Managerial Ability (*MA*) to explore how online channel adoption affects bank efficiency and risk depending on the managerial skill of adopting banks. In the spirit of Demerjian et al. (2012, 2013), we perform a Tobit regression of profit efficiency on the set of bank-level characteristics used in Equation (4), i.e., X_{it}. The residual of this Tobit regression informs the profitability driven by managerial ability rather than outputs, inputs, risk and other bank characteristics.

Panel B of Table 5 reports the results of Equation (7), where the coefficients of *ONLINE X MA* are significantly positive in Columns 2 and 4-6. First, adopting banks with a higher managerial ability are more able to use online channel adoption to reduce cost but are less pressed to develop fee-based income. Second, adopting banks with a higher managerial ability to generate profit are more capable of using online channel adoption to increase their capital from profitable investment and lending. As a result, those adopting banks use online channel adoption to increase *CAR* and reduce solvency risk.

Second, we set SOURCE = *Foreign*, which is a binary variable equal to one if a bank is owned by foreign investors, and zero otherwise. This specification explores how online channel adoption affects bank efficiency and risk depending on foreign investors of the adopting banks. Panel C of Table 5 reports the coefficients of *ONLINE X Foreign* are significantly positive in Columns 2 and 6. These results suggest that adopting banks with foreign investors are more capable of using online channel adoption to reduce cost. This approach may increase retained earnings from cost saving, which in turn increases *CAR*. These results are consistent with the enhancing effect of foreign ownership on bank efficiency reported in Berger et al. (2009), Jiang et al. (2013), and Sun et al. (2013).

5.3.3 Labour Intensity

We set SOURCE = *Employee/Asset* to measure the labour intensity of banks. This specification explores how online channel adoption affects bank efficiency and risk for banks with a higher labour intensity. Panel D of Table 5 reports the results of Equation (7), where the coefficients of *ONLINE X (Employee/Asset)* are significantly positive in Column 6. These results suggest that the labour-intensive adopting banks decrease their capital adequacy less than do the other adopting banks. Since the labour-intensive adopting banks rely more on interest income (see Columns 3-4), they reduce CAR less as a means for a buffer.

In summary, our results suggest that there are risk-return trade-off heterogeneities from adopting online channels across banks depending on their sizes, management skills and labour intensities.

5.3.4 Intensity of Online Channel Adoption

In this subsection, we explore the intensity effects of online channel adoption on bank efficiency and risk. Amid the development of online channel adoption, an increasing number of banks allow consumers to access online channels with their mobile phones and through WeChat. We view mobile banking and WeChat banking as two new types of online channel. We construct an intensity variable *#ONLINE* equal to 0, 1, 2, or 3 when a bank offers none, one, two or three types of internet, mobile, or WeChat banking services, respectively. In fact, banks will first deploy online channels and then mobile banking. WeChat banking is the last to be launched by banks. The lower panel of Figure 2 depicts that, since the year 2011, with the development of mobile terminals, an increasing number of banks started to deploy mobile banking and WeChat banking to upgrade their services. In 2016, the portions of banks with two and three online channels are 21% and 67%, respectively.

We set SOURCE = *#ONLINE* to measure the intensity of online channel adoption. Panel E of Table 5 reports the results of Equation (7), where the coefficients of *ONLINE X #ONLINE* are significantly negative in Columns 2, 3 and 6. Our results suggest that the adopting banks incur marketing expenses to promote (DeYoung and Duffy 2004) and personnel expenses to maintain the services (DeYoung et al., 2007). Additionally, the expansion of online channel adoption does not promote interest income, which may be driven by the intense competition among adopting banks. Consequently, the CAR decreases, possibly because of lower retained earnings. In summary, the adopting banks do not benefit more from a higher intensity of online channel adoption, which suggests that content enrichment only serves as a standard competitive tool rather than a competitive edge for the adopting banks.

6. Conclusion

This paper examines the adoption of online channels and the effects of online channel adoption on bank performance based on a sample of Chinese banks. We find that online channel adoption depends on size, financial performance, business strategy, competition, and demographics. Further, our empirical results show that online channel adoption improves the profit efficiency of the adopting banks, which can be attributed to the rise in non-interest income efficiency, even though cost efficiency deteriorates. This finding suggests that online banking adoption promotes new development of a business model, which increases the efficiency of generating non-interest income through fee-based services. However, the new business model potentially relates to the additional marketing, personnel and depreciation expenses. Turning to risk management, online channel adoption weakens the loan quality of the adopting banks, which also raises their solvency risk. Overall, profit efficiency increases as the adopting banks find the rise in non-interest income outweighs the fall in cost efficiency. Since there are joint effects of risk and return from adopting online channels, our results suggest that online channel adoption alters the risk-return trade-off of the adopting banks. Banks with a smaller size, better management skills and a higher labour intensity benefit more from adopting online channels because they face a weaker risk-return trade-off from adopting online channels. However, the costly content enrichment of online channels, which seems to be a competitive tool among banks, does not benefit the adopting banks. Our results pass a series of robustness checks, including alternative variable definitions, alternative specifications, omitted variable biases, and sample selection.

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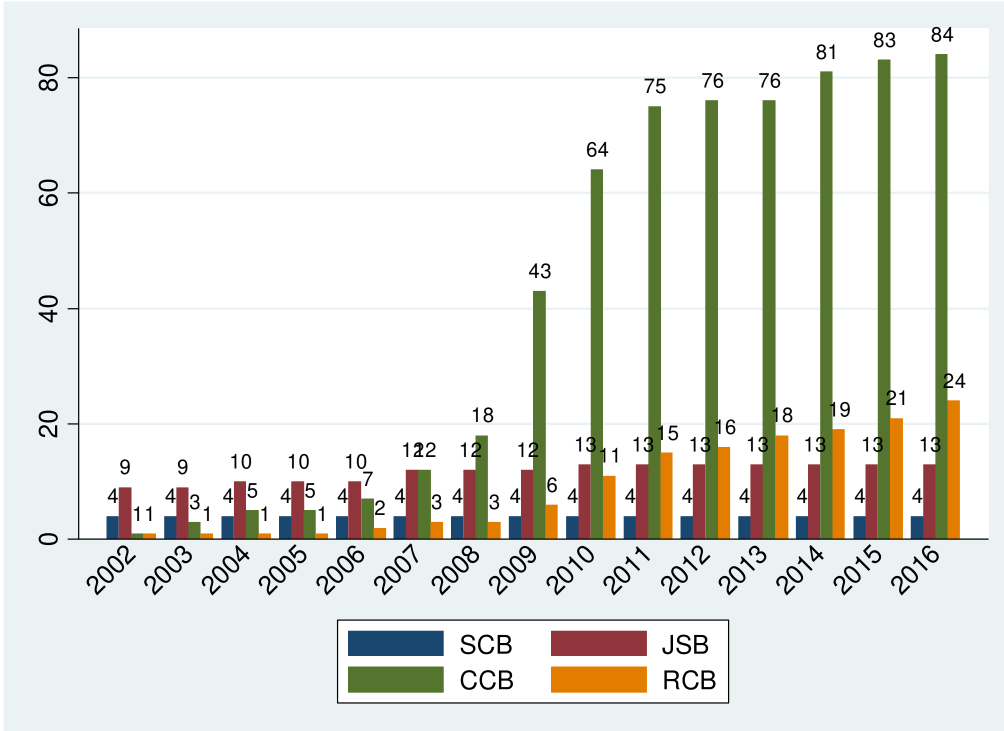

Fig.1. Number of Banks adopting Online channel

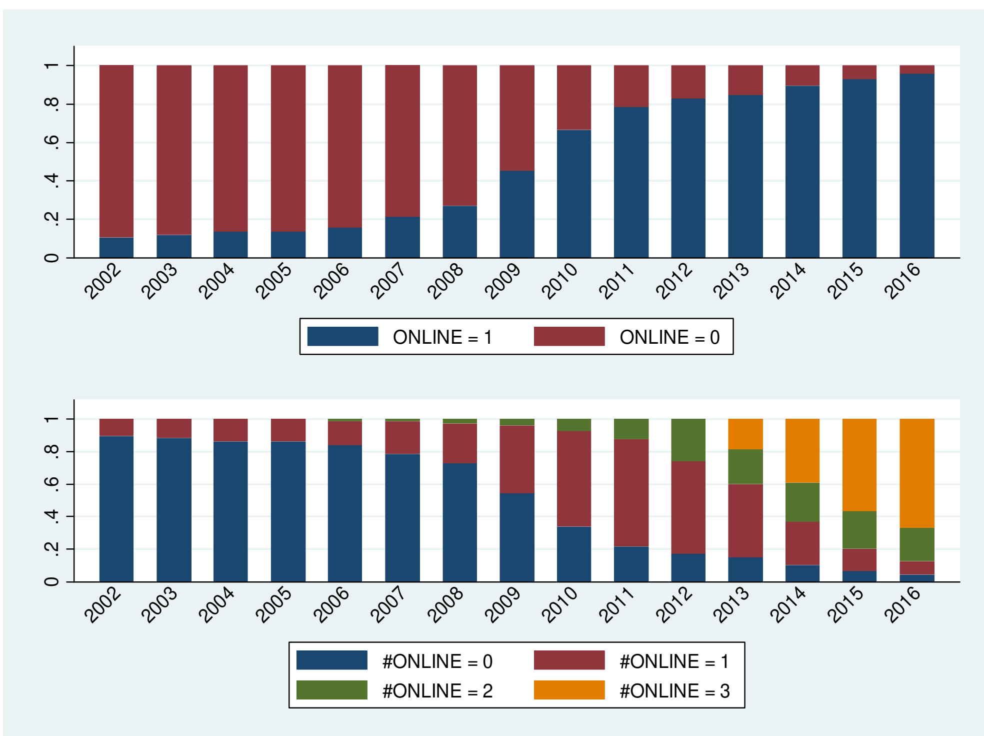

Fig.2. Evolution of ONLINE and #ONLINE by Year

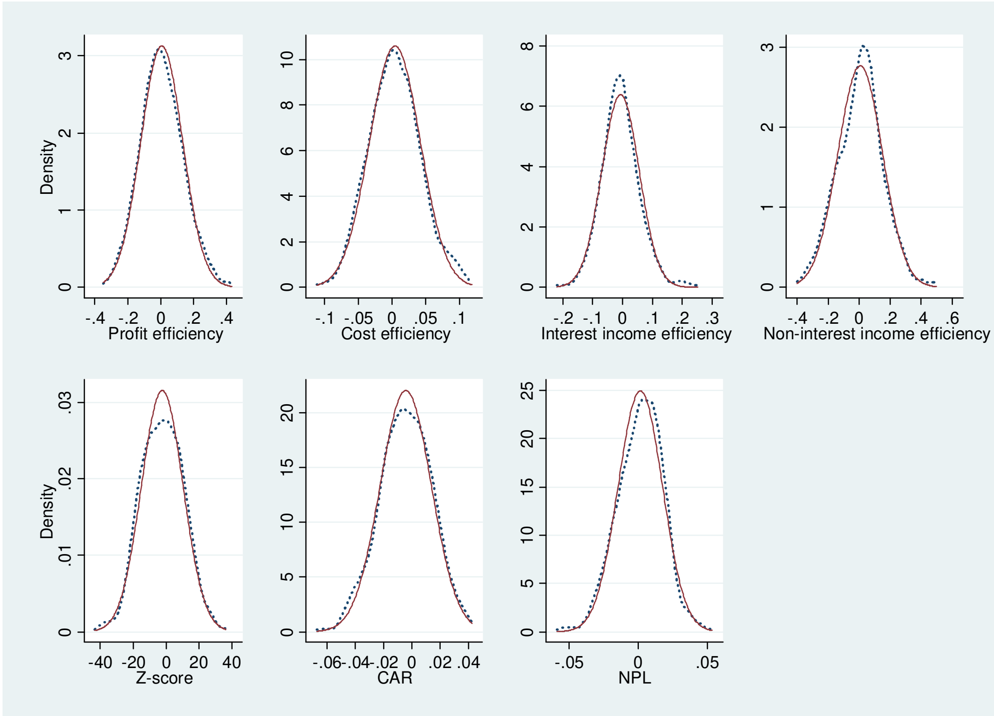

Fig.3. Placebo Tests

Note: To preserve the numbers of banks deploying online channel in each sample year as depicted in Figure 1, we randomly assign the same number of banks as the treatment group without replacement in each year.

The p-value for testing the null hypothesis that the median of coefficients of PLACEBO-ONLINE is zero are (from left-highest to right-lowest) 0.614 (PE), 0.397 (CE), 0.130 (IIE), 0.256 (NIE), 0.343 (Z-score), 0.950 (CAR) and 0.114 (NPL).

The p-value for testing the null hypothesis that the mean of coefficients of PLACEBO-ONLINE is zero are (from left-highest to right-lowest) 0.152 (PE), 0.103 (CE), 0.248 (IIE), 0.702 (NIE), 0.302 (Z-Score), 0.404 (CAR) and 0.399 (NPL).

Table 1 Distribution of observations

Year	Total Observations	By Ownership				By Adopter		
		SCB	JSB	CCB	RCB	Early	Recent	Non
2002	2	0	2	0	0	2	0	0
2003	5	2	3	0	0	4	1	0
2004	7	3	4	0	0	6	1	0
2005	10	3	6	0	1	8	2	0
2006	14	3	7	3	1	11	3	0
2007	17	4	7	5	1	13	4	0
2008	26	4	10	9	3	18	8	0
2009	37	4	11	17	5	23	14	0
2010	49	4	13	25	7	31	18	0
2011	63	4	13	36	10	43	19	1
2012	80	4	13	47	16	53	22	5
2013	98	4	13	60	21	66	25	7
2014	103	4	13	63	23	69	25	9
2015	92	4	13	52	21	63	21	6
2016	102	4	13	64	21	72	23	7
Total	703	51	141	381	130	482	186	35

No. of Banks	By Adopter		
By Ownership	Early	Recent	Non
SCB	4	0	0
JSB	12	1	0
CCB	54	13	8
RCB	12	10	4
Total	82	24	12

Notes: SCB, JSB, CCB and RCB are state commercial bank, joint-stock bank, city commercial bank and rural commercial bank, respectively. Early adopters are banks adopted online channel in or before its first year of observations. Recent adopters are banks adopted online channel after its first year of observations. Non-adopters are banks not yet adopted online channel until the last year of its observations.

Table 2 Descriptive Statistics

							Adopter		Non-Adopter		Difference	
Variable	Level	Obs	Mean	Min	Max	SD	Obs	Mean	Obs	Mean	Diff	P-val.
1. Dependent Variables												
PE	Bank	703	0.791	0.043	0.976	0.093	668	0.791	35	0.789	0.002	0.892
CE	Bank	703	0.939	0.401	0.990	0.031	668	0.939	35	0.940	-0.001	0.890
IIE	Bank	703	0.817	0.232	0.963	0.091	668	0.816	35	0.822	-0.006	0.717
NIE	Bank	677	0.653	0.104	0.891	0.103	645	0.654	32	0.628	0.025	0.174
Z-Score	Bank	676	38.43	2.025	204.0	17.40	641	38.23	35	42.10	-3.868	0.200
CAR	Bank	676	0.127	0.004	0.409	0.027	641	0.126	35	0.142	-0.016	0.001
NPL	Bank	703	0.016	0.000	0.382	0.024	668	0.016	35	0.014	0.002	0.603
2. Main explanatory variables												
ONLINE	Bank	703	0.870	0	1	0.336	668	0.916	35	0	0.916	0.000
#ONLINE	Bank	703	1.670	0	3	1.036	668	1.757	35	0	1.757	0.000
3. Control Variables												
SIZE	Bank	703	13769	90.03	236639	33327	668	14414	35	1451	12963	0.020
BRANCH	Bank	703	0.081	0.007	0.366	0.055	668	0.081	35	0.080	0.001	0.909
NCITY	Bank	703	42.001	1	341	87.63	668	43.88	35	6.143	37.74	0.012
HHI	Bank	703	0.177	0.074	0.606	0.071	668	0.178	35	0.155	0.022	0.069
PINC	Bank	703	25743	10954	54305	8860	668	25865	35	23422	2443	0.112
POP	Bank	703	829.6	106.0	3392	562.6	668	848.6	35	466.6	382	0.000
NFIRM	Bank	703	4515	223	18792	3349	668	4619	35	2523	2096	0.000

Notes: Definition and unit of variables are reported in Appendix 1. Variables are adjusted for inflation using the CPI, with 2002 as the base year. The observation of highest liquidity (1.061) is winsorized with the second largest value (0.933). The sub-sample of Adopter are all observations from early and recent adopting banks. See the notes of Table 1 for definitions of adopters.

Table 3: Benchmark Results and its Identification

	(1) PE	(2) CE	(3) IIE	(4) NIE	(5) Z-Score	(6) CAR	(7) NPL
Panel A: Full Sample							
ONLINE	0.0725	-0.0072	0.0909	0.134**	-19.80***	-0.00378	0.0264***
	(0.0471)	(0.0055)	(0.0997)	(0.0589)	(4.903)	(0.00586)	(0.0049)
lnSIZE	0.0206***	2.01e-06	0.00066	0.0053**	6.032***	0.000750	0.0008
	(0.00640)	(0.0016)	(0.00248)	(0.0013)	(0.442)	(0.00123)	(0.0018)
BRANCH	0.174***	-0.0923**	0.205**	0.24*	-66.42	-0.0454	0.0514*
	(0.0515)	(0.038)	(0.0920)	(0.127)	(63.36)	(0.0625)	(0.0293)
lnNCITY	-0.0220***	-0.00081	-0.00652	-0.0082	-0.339	-0.000980	-0.0026
	(0.00622)	(0.0016)	(0.00542)	(0.0062)	(1.136)	(0.00224)	(0.0026)
HHI	0.00961	-0.019***	-0.0182	-0.0941*	16.46*	-0.00336	-0.016**
	(0.0491)	(0.0064)	(0.0303)	(0.057)	(9.226)	(0.00601)	(0.0066)
lnPINC	-0.0400	-0.0028**	-0.0141	0.0058	4.372*	-0.00316	0.0007
	(0.0315)	(0.0011)	(0.0158)	(0.0147)	(2.259)	(0.00616)	(0.0033)
lnPOP	0.00693	0.0007	0.00270	-0.0228***	3.815***	-0.00402***	-0.0009
	(0.00887)	(0.0017)	(0.00598)	(0.008)	(1.039)	(0.00118)	(0.0009)
lnNFIRM	-0.0119***	0.0012	0.00413	0.0139***	0.692	0.00208***	-0.0014***
	(0.00269)	(0.0012)	(0.00310)	(0.0035)	(0.471)	(0.000754)	(0.0005)
GR	-0.0524**	-0.0012	-0.061	-0.085***	9.611**	0.001	-0.018***
	(0.0263)	(0.0014)	(0.054)	(0.032)	(3.311)	(0.003)	(0.0057)
Observations	569	569	569	549	551	551	569
Panel B: Recent + Non Adopters							
ONLINE	0.123***	-0.0109	0.152*	0.0852**	-14.85***	-0.0121**	0.031***
	(0.0369)	(0.0074)	(0.0868)	(0.0376)	(2.990)	(0.005)	(0.0091)
GR	-0.099***	0.0073**	-0.1044	-0.0647**	6.849***	0.0036***	-0.027
	(0.0224)	(0.0032)	(0.6657)	(0.0252)	(0.952)	(0.0003)	(0.027)
Observations	177	177	177	174	172	172	177
Panel C: Early + Recent Adopters							
ONLINE	-0.0562**	-0.0099	-0.0009	0.0740	-9.593***	-0.0066	0.0273***
	(0.0282)	(0.0198)	(0.0495)	(0.397)	(3.17)	(0.0046)	(0.0039)
GR	-0.0359**	0.002	0.0115	-0.073	2.055	-0.0005	-0.0181**
	(0.0164)	(0.0053)	(0.016)	(0.245)	(2.128)	(0.0012)	(0.0078)
Observations	547	547	547	528	529	529	547
Year FE	√	√	√	√	√	√	√
Bank-type FE	√	√	√	√	√	√	√
Bank-type Trend	√	√	√	√	√	√	√

Notes: The dependent variables are listed at the top of each column. Panels B and C include the same set of control variables as in Panel A, but omitted in this table for brevity. Standard errors are clustered at bank-type level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Robustness Checks

	(1) PE	(2) CE	(3) IIE	(4) NIE	(5) Z-Score	(6) CAR	(7) NPL
Panel A: Dynamic Effects							
ONLINE	0.0151	0.00552	0.109	0.141	-21.03***	-0.00585	0.0211***
	(0.0451)	(0.0108)	(0.0996)	(0.123)	(6.611)	(0.00851)	(0.0009)
ONLINE (t+1 & t+2)	0.0499***	-0.0116	-0.0221	-0.0218	1.181	0.000486	0.0102***
	(0.0186)	(0.0101)	(0.0358)	(0.0349)	(2.816)	(0.00423)	(0.001)
ONLINE (t+3 & t+4)	0.0670***	-0.0145***	-0.000343	-0.0188	1.867	0.00556	0.0007
	(0.0258)	(0.00501)	(0.0303)	(0.0431)	(1.175)	(0.00426)	(0.0008)
ONLINE (≥ t+5)	0.0579**	-0.0116***	-0.0202	-0.0318	0.943	-0.000359	0.0071***
	(0.0227)	(0.00417)	(0.0274)	(0.0320)	(2.534)	(0.00191)	(0.002)
Observations	569	569	569	549	551	551	569
Panel B: Sample Selection							
ONLINE	0.0646	-0.006	0.0884	0.127**	-18.47***	-0.00239	0.0278
	(0.0533)	(0.0055)	(0.0908)	(0.061)	(5.918)	(0.00589)	(0.0215)
Observations	561	561	561	541	543	543	561
Panel C: Additional Control Variables							
ONLINE	0.0723	-0.0086*	0.0908	0.132*	-19.79***	-0.0035	0.0272***
	(0.0483)	(0.0051)	(0.119)	(0.0628)	(5.291)	(0.005)	(0.056)
Observations	569	569	569	549	551	551	569
Panel D: Alternative Measures							
ONLINE	0.181	-0.142	0.145	0.284	-0.203***		
	(0.122)	(0.0953)	(0.244)	(0.214)	(0.0732)		
Observations	569	569	569	549	551		
Panel E: IV Estimation							
ONLINE	0.602***	-0.0132	0.295**	0.500	16.05	0.0240	-0.154***
	(0.198)	(0.0446)	(0.148)	(0.470)	(11.00)	(0.0309)	(0.0488)
Over-identification (p-value)	0.746	0.293	0.433	0.122	0.14	0.096	0.638
Under-identification (p-value)	0.000	0.000	0.000	0.109	0.000	0.000	0.000
Weak-identification (F-stat)	7.207	7.207	7.207	1.332	7.711	7.711	7.207
10% maximal IV size	19.93	19.93	19.93	19.93	19.93	19.93	19.93
Observations	693	693	693	668	666	666	693
Control Variables	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√
Bank-type FE	√	√	√	√	√	√	√
Bank-type Trend	√	√	√	√	√	√	√

Notes: The dependent variables are listed at the top of each column. Control variables include lnSIZE, BRANCH, lnNCITY, HHI, lnPCGDP, lnPOP, lnNFIRM and GR. The IVs used in Panel D are Business/Consumer Loan Ratio and MMC. In the first stage, we estimate the following reduced-form Probit model for adoption of online channel:

$$ONLINE_{it} = 1[X_{it}\theta_1 + \theta_{21}Business/Consumer\ \ Loan_{it} + \theta_{22}MMC_{it} + v_t + v_b + v_b \times t + \mu_{it}]$$

The coefficient of Business/Consumer Loan Ratio is negative and significant, while the coefficient of MMC is insignificant. Standard errors are clustered at bank type-level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Heterogeneities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	PE	CE	IIE	NIE	Z-Score	CAR	NPL
Panel A							
ONLINE	-0.165***	0.0192***	-0.0822**	-0.0676*	-19.1**	-0.0324	0.0393***
	(0.0371)	(0.005)	(0.0415)	(0.0339)	(7.832)	(0.0213)	(0.0114)
ONLINE X 1{CCB or RCB}	0.245***	-0.0277***	0.183***	0.205***	-0.661	0.0303	-0.0117
	(0.0257)	(0.0074)	(0.0294)	(0.025)	(8.505)	(0.0202)	(0.0125)
Panel B							
ONLINE		-0.00542**	0.0839	0.115	-19.63***	-0.00224	0.0278***
		(0.00215)	(0.0785)	(0.272)	(5.655)	(0.00489)	(0.0041)
ONLINE X MA		0.0290**	0.0164	-0.194*	69.12***	0.0692***	0.00645
		(0.0147)	(0.139)	(0.117)	(5.238)	(0.00904)	(0.0271)
Panel C							
ONLINE	0.0714	-0.0091**	0.0692	0.118	-20.12***	-0.00441	0.0269***
	(0.0457)	(0.0046)	(0.137)	(0.011)	(4.737)	(0.00637)	(0.00263)
ONLINE X Foreign	-0.0181	0.0375***	-0.0319	0.013	0.122	0.0183***	-0.00213
	(0.0279)	(0.0119)	(0.0406)	(0.0518)	(3.998)	(0.00699)	(0.00375)
Panel D							
ONLINE	0.0631	-0.0032	0.0644	0.175	-22.38***	-0.0150*	0.0224***
	(0.0640)	(0.0036)	(0.0782)	(0.139)	(8.319)	(0.0089)	(0.0022)
ONLINE X (Employee/Asset)	0.00339	-0.00085	0.0119*	-0.0201*	1.070	0.0041***	0.0011
	(0.0084)	(0.00098)	(0.0067)	(0.0112)	(1.715)	(0.0015)	(0.0018)
Panel E							
ONLINE	0.0828	-0.00405	0.105	0.124	-17.38*	0.00142	0.0281*
	(0.0559)	(0.00494)	(0.0858)	(0.109)	(9.437)	(0.0061)	(0.0154)
ONLINE X #ONLINE	-0.00655	-0.00165***	-0.00701***	-0.00364	-0.331	-0.0027**	-0.0005
	(0.00615)	(0.0003)	(0.00207)	(0.00741)	(1.889)	(0.0012)	(0.0005)
Control Variables	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√
Bank-type FE	√	√	√	√	√	√	√
Bank-type Trend	√	√	√	√	√	√	√
Observations	569	569	569	549	551	551	569

Notes: The dependent variables are listed at the top of each column. Control variables include lnSIZE, BRANCH, lnNCITY, HHI, lnPCGDP, lnPOP, lnNFIRM and GR. Standard errors are clustered at bank type-level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix 1: Variable Definitions and Sources

Table A1: Variable definitions and sources

Name	Description	Data Source
Panel A. Dependent Variables		
Profit efficiency (PE)	Time-varying profit efficiency	Own estimation from SFA
Cost efficiency (CE)	Time-varying cost efficiency	Own estimation from SFA
Interest income efficiency (IIE)	Time-varying net interest income efficiency	Own estimation from SFA
Non-interest income efficiency (NIE)	Time-varying non-interest income efficiency	Own estimation from SFA
Z-score	(ROA+CAR) / sd(ROA)	Bankscope, bank annual reports
CAR	Capital adequacy ratio = Capital/Asset	Bankscope, bank annual reports
NPL	The ratio of non-performing loan to gross loan	Bankscope, bank annual reports
Panel B. Main explanatory variables		
ONLINE	Equals to 1 after the bank opening online channel, 0 otherwise	Bank annual reports
#ONLINE	Equals to 0, 1, 2, and 3 respectively when a bank offer none, one, two and three types of online channel services. Three types of services include internet, mobile and WeChat banking.	Bank annual reports
Panel C. Control Variables		
SIZE	Total assets (Million RMB)	Bankscope, bank annual reports
BRANCH	Total number of branches/Total asset (1/Million RMB)	Bankscope, bank annual reports
NCITY	Numbers of cities that a bank have branches	CBRC website
HHI	Herfindahl-Hirschman Index measured by branch numbers in a city	Own calculation
PINC	Per capita income of city (10 thousand RMB/person)	National Bureau of Statistics of China
POP	Population of city (10 thousand)	National Bureau of Statistics of China
NFIRM	Number of firms in the city	National Bureau of Statistics of China

Appendix 2: First Stage Model for Online Channel Adoption

In this appendix, we discuss the specification of Equation (2), which is the first stage model for online channel adoption. In this specification, there are five sets of variables included in *X* (also used in the second stage model) and *Z* (only used in the first stage as IVs) capturing the following five dimensions: size, financial performance, business strategy, competition, and demographics.

First, we include two variables related to the scales of a bank, *SIZE* and *BRANCH*. *SIZE* is expected to have a positive relationship with *ONLINE* because larger banks may have more financial resources to adopt online channel. There is also a potential scale effect in adopting online channel, where the cost of adopting online channel does not depend on size. Consistently, previous studies show a positive effect of bank size on online channel adoption (Egland et al.,1998; Courchane et al., 2002; Corricher 2006; DeYoung et al., 2007; Hernando and Nieto 2007; Ciciretti et al. 2009; Hernandez-Mutillo et al., 2010; Onay and Ozsoz 2013; Pana et al., 2015; Dandapani et al., 2016). Further, BRANCH is defined as the ratio of number of branches over total assets. We employ this variable to examine the substitution or complement effects of branches on online channel adoption (Corricher 2006; Ciciretti et al., 2009; Hernandez-Mutillo et al., 2010). On one hand, banks substitute their branches with online channel to reduce cost, suggesting a negative effect of BRANCH on ONLINE. On the other hand, banks utilize online channel as a value-added service to complement their existing branch services, suggesting a positive effect of BRANCH on ONLINE. Nonetheless, the previous studies show the substitution effect of branches on the adoption of online channel.

Second, we include a set of financial indicators of banks, i.e., return on assets (ROA) and non-performing loan (NPL). A higher ROA and a lower NPL indicates a healthier financial situation of banks. There are mixed predictions on online channel adoption for banks with healthier financial situations. On one hand, they have more financial resources to adopt online channel. On the other hand, they are less motivated to adopt online channel to get customers. Previous studies also find mixed results. Some studies show that banks that are more profitable are more likely to deploy online channel (DeYoung et al., 2007; Ciciretti et al., 2009; Pana et al., 2015), while the other studies show that banks that are less profitable are more likely to adopt online channel (Hernandez-Murillo et al., 2010, Pana et al., 2015). Nonetheless, previous studies show that banks that have lower loan quality are less likely to adopt online channel (Ciciretti et al., 2009, Hernandez-Murillo et al., 2010; Pana et al., 2015, Dandapani et al., 2016).

Third, we include a set of variables capturing business strategy of banks, namely, Loan/Asset, Non-Interest Expenses Ratio, Non-Interest Income Ratio and Business/Consumer Loan. They measure how business strategy of a bank affecting its adoption of online channel. Previous studies show that loans/assets promote online channel adoption (Hernandez-Murillo et al., 2010; Pana et al., 2015); the non-interest expenses ratio and non-interest income ratio promote online channel adoption (Corricher 2006, DeYoung et al., 2007); and business/consumer loans affect online channel adoption ambiguously (Ciciretti et al., 2009, Dandapani et al., 2016). We also include NCITY as a bank strategy that may affect online channel adoption. Banks with consumers from different provinces may use online channel to promote their consumer satisfaction; for example, consumers make payments with online channel instead of visiting branches.

Fourth, we include several variables to proxy the effects of competition on online channel adoption. First, we include HHI (Courchane et al., 2002; DeYoung et al., 2007; Hernandez-Mutillo et al., 2010; Dandapani et al., 2016). Previous studies suggest that banks facing more competition are more likely to adopt online channel in order to increase their competitiveness. Second, we examine whether the adoption of online channel is affected by the adoption decision of competitors (DeYoung et al., 2007, Hernandez-Mutillo et al., 2010). Following Hernandez-Mutillo et al (2010), we construct the multimarket contact index (MMC) as follows:

$$MMC_i = \sum_{s \in M_i} \frac{BRANCH_{is}}{\sum_{r \in M_i} BRANCH_{ir}} \times \sum_{j \in B_s \setminus \{i\}} I_j \frac{BRANCH_{js}}{\sum_{k \in B_s} BRANCH_{ks}}$$

where M_i is the set of markets in which =bank i has operations, and market is defined as a province. B_s is the set of branches in market s. $BRANCH_{js}$ denotes the number of branches of bank j in market s. The indicator function I_j takes the value of 1 if bank j has adopted online channel in a previous period and 0 otherwise. The *MMC* index can be interpreted as the share of branches owned by the competitor of bank i that have already adopted online channel in the markets in which this bank operates.

Finally, our discussion on institutional backgrounds in the previous section suggests that economic development, consumers' characteristics (such as education and age), and internet infrastructure affect online channel adoption. Those variables are broadly consistent with a higher return, lower uncertainty, and lower cost in adopting a new technology based on Jensen (1982). Further, previous studies find income, education, age and internet infrastructure affect the adoption decision of internet banking (Egland et al.,1998, Courchane et al., 2002, Corricher 2006, DeYoung et al., 2007, Hernando and Nieto 2007, Ciciretti et al. 2009, Hernandez-Mutillo et al., 2010, Dandapani et al., 2016). We include economic and demographic variables, namely *PINC, POP, NFIRM, INTERNET, EDUCATION* and *AGE*, to capture unobserved heterogeneities across banks and years.

Table A2-1 reports the definitions and descriptive statistics of variables only used in the first stage. Table A2-2 reports the results of Equation (2), where all explanatory variables are lagged for one year. Columns 1-4 add the explanatory variables block-by-block and find the coefficients are robust across columns. Thus, we focus our discussion on the full specification reported in Column 4. The coefficients of *SIZE* are positive and significant, which shows that larger banks are more likely to deploy online channel, i.e. scale effect. The coefficient of *BRANCH* is negative and significant, which means that online channel is a substitute for physical branches. The coefficients of *ROA* are positive and significant, which shows a strong positive relationship between online channel adoption and financial resources. In contrast to the existing finding, the coefficients of *NPL* are positive and significant, which suggests that risker banks are more likely to adopt online channel (potentially for developing new business). The coefficients of *Loan/Asset* and *Non-interest Income Ratio* are significantly positive, while the coefficients of *Business/Consumer Loan* are significantly negative. These results are consistent with the existing findings.

From the perspective of competition, the coefficient of *HHI*, unlike Hernandez-Mutillo et al. (2010), is positive and significant. The results mean that banks with more market power tend to adopt online channel. Moreover, the coefficient of *MMC* is positive and significant. Our results suggest that banks' adoption of online channel is affected by the adoption decision of competitors, which is similar to the results for U.S. banks (DeYoung et al., 2007; Hernandez-Mutillo et al., 2010). Turning to the demographic variables, we only find that the coefficients of *lnPOP* are positive and statistically significant. However, we do not interpret this result literally because demographic variables are correlated with each other and only serve as control variables for economic development.

Overall, our results suggest that bank size (in asset and branch), financial resources, bank strategy, competition among banks, and demographics are determinants of online channel adoption in China. Further, the first stage specification provides several exclusion restrictions by lagging all the explanatory variables and including some significant IVs, such as *Business/Consumer Loan Ratio* and *MMC*, for estimating Equation (4) with the control function approach.

Table A2-1 Definitions and descriptive statistics of variables only used in the first stage

Variable	Description	Level	Mean	SD
ROA	Return on assets	Bank	0.013	0.005
Loan/Asset	Total loan / Total asset	Bank	0.467	0.182
Non-Interest Exp. Ratio	Non-interest expenses / Total expenses	Bank	0.327	0.096
Non-Interest Inc. Ratio	Non-interest income / Total income	Bank	0.079	0.083
Business/Consumer Loan	Business loan / Consumer loan	Bank	10.80	18.69
MMC	Multimarket contact index	Bank	0.992	0.179
EDUCATION	Fraction of population with college degree or higher	Province	0.163	0.096
AGE	Fraction of people aged 15-64 years	Province	0.761	0.094
INTERNET	Fraction of population available to internet	Province	0.474	0.148

Observation = 703. Data sources: Bankscope and bank annual reports (Bank-level variables); CBRC website and own calculation (MMC); National Bureau of Statistics of China (Provincial-level variables).

Table A2-2: Online channel adoption

	(1)	(2)	(3)	(4)
	ONLINE	ONLINE	ONLINE	ONLINE
lnSIZE	0.571***	0.577***	0.667***	0.743***
	(0.181)	(0.205)	(0.198)	(0.0661)
BRANCH	-2.870***	-3.025**	-5.423***	-4.266**
	(0.615)	(1.523)	(1.134)	(2.140)
ROA		14.11	7.743	37.61**
		(26.80)	(26.88)	(17.75)
NPL		8.057***	8.256***	10.72*
		(3.036)	(2.653)	(5.698)
Loan/Asset		3.803***	5.241***	4.352***
		(1.304)	(0.765)	(1.558)
Non-Interest Expenses Ratio		-2.908	-3.341	-3.342
		(2.588)	(2.725)	(2.590)
Non-Interest Income Ratio		3.632**	3.089**	2.960***
		(1.734)	(1.548)	(0.265)
Business/Consumer Loan		-0.00289	-0.00394***	-0.00431**
		(0.00252)	(0.00152)	(0.00187)
lnNCITY		0.159	0.131***	-0.0270
		(0.136)	(0.0324)	(0.0764)
HHI			4.646**	8.873***
			(2.102)	(2.839)
MMC			0.824	2.748***
			(0.765)	(0.390)
lnPINC				2.740
				(2.078)
lnPOP				0.440***
				(0.0230)
lnNFIRM				0.299
				(0.314)
INTERNET				-3.380
				(3.494)
EDUCATION				2.209
				(1.476)
AGE				-2.409
				(5.266)
Year FE	√	√	√	√
Bank-type FE	√	√	√	√
Bank-type Trend	√	√	√	√
Observations	515	515	515	515

Notes: All explanatory variables are lagged for one year. Control variables include lnPINC, lnPOP, lnNFIRM, INTERNET, EDUCATION and AGE. Also, SCBs and several year fixed effects perfectly predict the dependent variable. Thus, the number of observation is fewer than Table 3. Standard errors are clustered at bank type-level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix 3: Details of Stochastic Frontier Analysis (SFA)

We employ parametric SFA to estimate bank efficiency.[16] Particularly, we consider the following four error-component stochastic frontier model:

$$\ln\left(\frac{\pi}{w_2 z}\right)_{it} = \delta_0^* + \sum_{j=1}^{3}\delta_j \ln\left(\frac{y_j}{z}\right)_{it} + \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3}\delta_{jk}\ln\left(\frac{y_j}{z}\right)_{it}\ln\left(\frac{y_k}{z}\right)_{it} + \beta_1 \ln\left(\frac{w_1}{w_2}\right)_{it}$$

$$+\frac{1}{2}\beta_2 \ln\left(\frac{w_1}{w_2}\right)_{it}\ln\left(\frac{w_1}{w_2}\right)_{it} + \sum_{j=1}^{3}\gamma_j \ln\left(\frac{y_j}{z}\right)_{it}\ln\left(\frac{w_1}{w_2}\right)_{it} + \rho_1 NPL_{it} + \rho_2 NPL_{it}^2 + \alpha_t + \alpha_i + \varepsilon_{it} \qquad \text{(A1)}$$

The dependent variable π represents the bank's profit before taxes normalized by total assets (*z*) and a price factor w_2 (to be defined later) of bank i at time t. We follow Berger and Mester (1997) and Berger et al. (2009) in normalizing profit and output variables by total assets (*z*) for comparing across banks with different sizes. We also impose the homogeneity of input prices in the frontier function, which imposes several constraints on parameters.

Following the intermediation approach (Sealey and Lindley, 1977), three outputs (y_1, y_2, y_3) are considered here: total deposits y_1, total loans y_2 and total investments y_3. Two factor prices are also included in our model. One is the average deposit interest rate (w_1) to measure the price of funding input. The other is the price of other inputs (w_2) including employment and fixed assets. Since total expenses on employees are not available for most banks, we follow Hasan and Marton (2003) to use the ratio of total non-interest expenses to total fixed assets to proxy the price of non-fund input. *NPL* is the non-performing loan ratio, i.e. the ratio of impaired loans to gross loans, which controls either for risk taking or output quality (Berger and Humphrey 1997; Hughes and Mester 2010). Year fixed effects are included to control the potentially linear trend in bank efficiency due to technological progress.

In Equation (A1), The intercept term is transformed to be $\delta_0^* = \delta_0 - E(u_{it}) - E(\eta_i)$. The regression decomposes the error into two components, namely a time-varying component $\varepsilon_{it} = v_{it} - u_{it} + E(u_{it})$, and a

[16] One advantage of using SFA is that it allows the separation of inefficiency from random shocks or measurement errors and, thus, avoids overestimating inefficiency. However, this feature comes at a cost of specifying a functional form for the frontier, which motivates some studies employ another commonly used technique, i.e. data envelop analysis (DEA) (Berger and Humphrey 1997; Hughes and Mester 2010)

time-invariant component $\alpha_i = \mu_i - \eta_i + E(\eta_i)$. In this specification, α_i and ε_{it} have zero mean and constant variance. There are four error components. The variables μ_i and v_{it} represent bank-specific time-variant and time-varying heterogeneities of the frontier function. These two components are assumed to be independently and identically distributed as a normal distribution with mean zero and constant variance. The variable η_i and u_{it} are the non-negative random variables capturing time-invariant and time-varying inefficiencies. They are assumed to follow independently and identically distributed truncated normal distributions. These specifications allow bank efficiency measures to be bank-specific and dependent on evolving macroeconomic conditions.

The time-varying, instead of time-invariant, bank profit efficiency is used to assess the implications of online channel on overall efficiency. Observations of the time-varying bank profit efficiency: $E[e^{-u_{it}}|v_{it} - u_{it} + E(u_{it})]$ are generated from the results of estimating Equation (A1) using the multi-step procedure suggested by Kumbhakar et al. (2014). In addition to profit efficiency, we consider cost, non-interest income and interest income efficiencies. These alternative efficiency measures shed a light on possible sources of changes in profit efficiency. Equation (A1), with the profits before taxes variable (π) replaced with total costs, (net) interest income, total non-interest income, is used to generated observations on these alternative efficiency measures as discussed above.[17] The efficiency measure assumes a value between zero to one; with one implies the highest level of efficiency and zero the lowest level.

First, we estimate Equation (A1) with the standard random effect panel regression to obtain the predicted values of $v_{it} - u_{it}$ and $\mu_i - \eta_i$. Second, the time-varying technical inefficiency is estimated with the predicted value of ε_{it} from the first step, i.e. $\widehat{\varepsilon_{it}} = v_{it} - u_{it} + E(u_{it})$. In the specification, v_{it} is i.i.d. $N(0,\sigma_v^2)$ and u_{it} is $N^+(0,\sigma_u^2)$, which means $E(u_{it}) = (\sqrt{2/\pi}\sigma_u)$, and ignoring the difference between the true and predicted values of ε_{it}. Then, we employ the standard stochastic frontier technique to obtain the estimates of time-variant technical inefficiency components using Battese and Coelli (1988) procedure, i.e. $RTE = exp\ (-u_{it}|\varepsilon_{it})$. Third, we estimate time-invariant inefficiency following a similar procedure as in the second step. The time-invariant technical inefficiency is estimated with the predicted value of α_i from the first step, i.e. $\widehat{\alpha_i} = \mu_i - \eta_i + E(\eta_i)$. We assume μ_i is i.i.d. $N(0,\sigma_\mu^2)$, η_i is i.i.d. $N^+(0,\sigma_\eta^2)$, which in turn means $E(\eta_{it}) = (\sqrt{2/\pi}\sigma_\eta)$, and ignoring the

[17] An inefficiency term is added to, rather than subtracted from, the cost frontier function. It means that the higher the cost the less efficient a bank is. Further, a positive constant is added to the non-interest income efficiency estimation equation to avoid taking logarithm of a negative number. Our results on non-interest income efficiency are robustness to the magnitude of positive constant added to the frontier function. The results are available upon request.

difference between the true and predicted values of α_i. Then, we employ the standard stochastic frontier technique to obtain the estimates of time-invariant technical inefficiency components using Battese and Coelli (1988) procedure, i.e. PTE=exp(-$\eta_i|\alpha_i$).

The overall technical efficiency is obtained from the product of PTE and RTE, i.e. $OTE = PTE \times RTE$. Overall, the distributional assumptions on the inefficiency terms allow the persistent inefficiency and variable inefficiency to be identified. Table A3-1 reports the descriptive statistics of variables used in the efficiency estimation. Table A3-2 reports the parameter estimates of translog function for profit (π), cost (c), (net) interest income efficiencies (ninc), non-interest income (inc). The time-variant and time-invariant inefficiency components are significant, which supports the use of this four error-component stochastic frontier model.

Figure A1 shows the average year-by-year (time-varying) efficiency scores. In general, the four efficiency measures remain steady over the sample period. Profit efficiency was lowest in 2007 at 77.2% and peaked in 2015 at 80.2%. Cost efficiency stays stable at 92% to 94% over the sample period. Similarly, interest income efficiency also shows the same pattern since cost efficiency fluctuates from 81% to 83%. Non-interest income efficiency decreases by 1 percentage points, from 65% in 2004 to 64% in 2016.

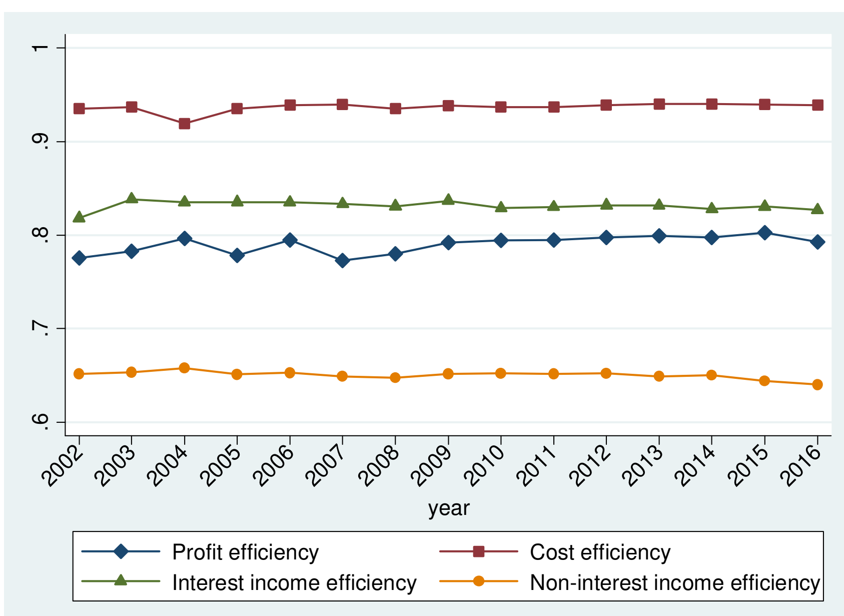

Fig.A1. Evolution of (time-varying) efficiency scores by year

Table A3-1 Definitions and descriptive statistics of variables used in the efficiency estimation.

Variable	Description	Mean	SD
Profit (π)	Total profit	205.5	543.4
Total Costs (c)	Operating cost plus interest cost	379.5	862.9
Non-interest income (inc)	Non-interest income	368.7	863.5
Net interest income (ninc)	Interest income	56.04	178.2
Total Deposits (y_1)	Total deposits	12196	29283
Total loans (y_2)	Gross loans	6946	17586
Total investments (y_3)	Other earning assets	4954	10959
Price of funds (w_1)	Price of funds	0.024	0.008
Price of capital (w_2)	Price of labor	0.003	0.001
Total assets (z)	All assets listed on the asset side of balance sheet	13769	33327
NPL	The ratio of non-performing loan to gross loan	0.016	0.024

Observation = 703. Notes: All variables are at bank-level. Variables are adjusted for inflation using the CPI, with 2002 as the base year. All variables, excluding input prices and NPL, are in RMB Million. Data sources: Bankscope, bank annual reports.

Table A3-2 Parameter estimates of stochastic frontier models

Variables	PE	CE	IIE	NIE
Panel A: First Stage				
$\ln(y_1/z)$	-0.184	-0.602**	0.449	-1.967
	(0.905)	(0.257)	(0.729)	(2.135)
$\ln(y_2/z)$	0.456	0.672***	0.152	2.348*
	(0.539)	(0.153)	(0.434)	(1.258)
$\ln(y_3/z)$	0.188	0.206**	-0.411*	0.936
	(0.296)	(0.0840)	(0.238)	(0.694)
$\ln(w_1/w_2)$	0.387	0.477***	0.286	-0.601
	(0.287)	(0.0817)	(0.231)	(0.663)
$\ln(y_1/z)\ln(y_1/z)/2$	0.341	0.836***	-0.302	1.235
	(0.419)	(0.119)	(0.338)	(0.984)
$\ln(y_2/z)\ln(y_2/z)/2$	0.146	0.160**	0.175	-0.149
	(0.225)	(0.0639)	(0.181)	(0.522)
$\ln(y_3/z)\ln(y_3/z)/2$	-0.0242	-0.0284**	-0.119***	0.109
	(0.0389)	(0.0111)	(0.0314)	(0.0912)
$\ln(y_1/z)\ln(y_2/z)/2$	-1.111*	0.0263	1.632***	-4.162***
	(0.603)	(0.171)	(0.486)	(1.421)
$\ln(y_1/z)\ln(y_3/z)/2$	0.243	-0.669***	-0.145	1.916**
	(0.347)	(0.0987)	(0.280)	(0.815)
$\ln(y_2/z)\ln(y_3/z)/2$	0.327	0.111	0.112	1.459**
	(0.244)	(0.0694)	(0.197)	(0.569)
$\ln(w_1/w_2)\ln(w_1/w_2)/2$	0.0319	0.0663***	0.233***	0.146
	(0.0850)	(0.0241)	(0.0684)	(0.197)

$\ln(y_1/z)\ln(w_1/w_2)$	0.236	0.528***	0.135	1.155
	(0.303)	(0.0862)	(0.244)	(0.716)
$\ln(y_2/z)\ln(w_1/w_2)$	0.0579	-0.162***	0.287**	-0.909**
	(0.158)	(0.0450)	(0.127)	(0.368)
$\ln(y_3/z)\ln(w_1/w_2)$	-0.0417	-0.143***	-0.0131	-0.0816
	(0.0879)	(0.0250)	(0.0708)	(0.207)
NPL	-7.616***	-0.131	1.296	-1.807
	(1.438)	(0.409)	(1.158)	(3.576)
NPL^2	22.93***	-0.802	-4.875	9.871
	(4.833)	(1.373)	(3.893)	(11.82)
Year FE	Yes	Yes	Yes	Yes
Panel B: Second Stage				
Constant	0.2559***	-0.0672***	0.212***	0.4898***
	(0.0133)	(0.0039)	(0.0122)	(0.0588)
$\lambda_1=\sigma_u^2/(\sigma_u^2+\sigma_v^2)$	1.861***	1.5984***	1.846***	1.1023***
	(0.0215)	(0.006)	(0.0202)	(0.0946)
Log-Likelihood	-79.77	1050	98.50	-880.9
Panel C: Third Stage				
Constant	0.3003***	-0.1051***	-0.0283	0.041
	(0.0187)	(0.0071)	(0.1921)	(0.2069)
$\lambda_2=\sigma_\eta^2/(\sigma_\eta^2+\sigma_\mu^2)$	2.1909***	1.8999***	0.0153	0.0169
	(0.0338)	(0.0125)	(0.242)	(0.260)
Log-Likelihood	-235.6	873.3	-3.802	-562.9

Standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.