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碩士學位論文

P2P 借貸對於銀行績效影響

The Effects of P2P Lending on Bank Performance

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The Effects of P2P Lending on Bank Performance

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Abstract

With the development of technology, some tech companies already use financial technology to provide financial services to the public like P2P platforms. Will the development of P2P impacts on banks performance? and whether different operation models of P2P will lead to a different result? In this paper, we contribute to this ongoing issue by analyzing banks efficiency and performance before and after P2P showing up in both U.S and UK. First, we find U.S. and UK small time deposits (deposits less than $100,000) in commercial banks went down after 2008 the time which P2P grew up. Second, according to our empirical results, P2P overall makes negative impacts on banking system in the U.S. but not in UK, because the business model of P2P in the U.S. is more like a traditional bank. The result shows that the appearance of P2P indeed brings about the change of people's financial behavior in the U.S due to higher investment return for investors and lower borrowing cost for borrowers. People have more options to manage their money except saving at banks now, and it harms banks operation in that deposits and loans of banks gets lower than before. At the same time, however, input variables such as fixed assets and labors of banks are still growing, leading to bank efficiency and performance get worse than the time before P2P appearance. But there are also risks on P2P lending platforms such as default risk and the crackdown of P2P. Therefore, governments also have to monitor this issue. They can erect more restricted rules on P2P established, making sure that investors can have more protection.

JEL: G21, G23, L81, D53, G28
Keywords: *P2P Lending, Bank's Performance*

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1. Introduction

Peer-to-peer lending (P2P lending), is the practice of lending money to individuals or businesses through online services that match lenders with borrowers. The P2P lending industry started in February 2005 when the first P2P lending company, Zopa, was founded in the UK. In the US, P2P lending started in February 2006 with the launch of Prosper Marketplace, followed by LendingClub. A turning point in the recent history of P2P lending was the bankruptcy of Lehman Brothers in 2008. As people lost confidence in financial institutions and were no longer able to secure credit at a reasonable level of interest – P2P lending emerged as a viable alternative.[1]

Since P2P lending companies provide these services online, they can run with lower overhead and provide the service more cheaply than traditional financial institutions. P2P lending platforms provide lenders with online credit checking to help in screening high-risk borrowers (Einav et al. 2013), and this allows them to extend more generous loans to medium-risk borrowers and to reduce discriminatory biases (Bartlett et al. 2017). As a result, lenders can earn higher returns compared to savings and investment products offered by banks, while borrowers can borrow money at lower interest rates, even after the P2P lending company has taken a fee for providing the match-making platform and credit checking the borrower. (Yan, Yu, Zhao, 2015). The industry has been growing rapidly and currently, the largest markets are China, the United States and Europe. Across the world, there are thousands of platforms that have distributed billions worth of loans. According to Ozili (2018), since nearly 50% of people in developing world already own a mobile phone, expansion of digital finance such as online lending could lead to financial inclusion.

P2P lending not only serves those customers who were excluded from the traditional financial institutions and hence supports financial inclusion. It also provides alternative investment approach for the customers in the traditional financial services and for the financial institution themselves. Customers in the traditional banks may switch their deposits to invest in the P2P platforms for higher return. According to LendingClub, the largest P2P platform in the

[1] http://peersociallending.com/news/history-peer-peer-lending/

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US, traditional banks account for 49% of its investor distribution.

Hence, the effects of P2P lending on the performance of traditional banks are complex. While high risk borrowers turning to P2P lending as an alternative financing venue can reduce banks' overall credit risk, the outflow of depositors and borrowers from traditional banks to P2P lending platforms can be a curse for traditional banks. Although these potential impacts have been addressed conceptually, there is still little research providing evidence for the effects of P2P lending on the performance of traditional banks. An exception is De Roure, Pelizzon, and Tasca (2016) showing that banks' lending volumes are negatively correlated with the P2P lending volumes. We provide the first attempt to measure the effects of P2P lending on traditional banks' performance.

There are mainly two types of business models in P2P platforms. First, the P2P company serves as a dealer; Lenders deposits their money in a pool of fund, and the P2P company dispatches the money to different borrowers. In this model, lenders don't know the borrowers' information. The largest P2P company in the U.S., LendingClub, provides an influential example for the first model. Second, the P2P company serves as a match maker; It offers a platform for borrowers and lenders to match and make a deal directly and the platform only charges small membership and transaction fees. In this model, lenders can observe borrowers' information (Wang, Chen and Song, 2015). The largest P2P company in U.K., Zopa, provides an influential example for the second framework.

The intermediary role of P2P company in the first framework is similar to traditional banks. Therefore, in addition to the three aspects of influences on bank performance mentioned above, there can be a further negative impact from more competition in the first model. To justify this hypothesis, we study the effects of P2P lending on bank efficiency and performance for both US and UK.

We will evaluate the impacts of P2P on bank performance by using two-stage approach. In the first-stage, we calculate bank performance for the US and UK. Then in the second-stage, we regress bank performance on a firm-specific proxy for P2P lending while controlling for firm specific characteristics.

The regression models for the US and UK are a bit different due to different measures on

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the dependent variable. For the US, we run both Tobit and OLS models to estimate linear relationships between bank performance and the P2P lending variable. For the UK,[2] we run both OLS and panel data with random effect models to estimate linear relationships between bank performances and the P2P lending variable.

Most importantly, since P2P lending operates online, it has impacts on the entire banking system. We can collect transaction data for the two P2P lending companies, but there is no detailed location information of the lenders and borrowers to describe the potential firm-specific impacts. Also, a dummy variable indicating when P2P lending started cannot be used to measure its impact on individual banks, because it is difficult to isolate the impacts from the financial turmoil in 2008 and P2P lending.

Hence, to find a firm-specific proxy for p2p lending, we compare the annual lending volume of the P2P platform with every item in the income statements of the whole commercial banks. According to their similarity in time paths and the correlation coefficient, we choose "small time deposits" which are time deposits less than $100,000 in commercial banks as our firm-specific proxy for P2P lending effect in both UK and US. Figure 1 below shows the patterns of the annual lending volume of LendingClub and the levels of small time deposits of commercial banks in the U.S. The correlation between the two terms is -0.745, which indicates that P2P lending volume (LendingClub) is highly and negatively correlated with small time deposits of commercial banks in the U.S. As for the UK data, due to data unavailability, we have collected data from the websites of six major banks (HSBS, Barclays, Standard Chartered, Lloyds, Santander UK, and RBS). We compare the annual lending volume of Zopa with the total amount for every item in the income statements of six sample banks. Figure 2 shows the patterns of Zopa's annual lending volume and the sum of small time deposits of six sample banks. The correlation between the two terms is -0.421, which indicates that P2P lending (Zopa) lending volume is negatively correlated with the total sum of small time deposits of our six commercial banks in the U.K.

When calculating the efficiency scores for the US banks, since P2P lending will affect

[2] Observations for several variables used to calculate the efficiency scores are missing in the UK dataset of BankFocus (previously named Bankscope).

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commercial banks' loans and deposits, we use two different groups of output variables to distinguish the effects of P2P lending on loan efficiency and deposit efficiency. For each model, we calculate the technical efficiency scores (TE), and the pure technical efficiency scores (PTE) to measure the "scale efficiency" and "managerial efficiency", respectively (see Charnes et al., 1978; Banker et al., 1984). Moreover, to examine whether the effects of P2P lending change with the banking scale, we follow Wolfe and Yoo (2018) in classifying banks with total assets greater than US$300 million as "large banks" and those with total assets under US$300 million as "small banks".

We can conclude the impacts on the US banks from two aspects. First, in terms of loan efficiency, P2P lending has negative effects on both small banks' scale and managerial loan efficiency. Differently, P2P lending has a negative impact on large banks' scale efficiency but a positive impact on large banks' managerial efficiency in loans. Our results also show that the magnitudes of P2P lending effect are higher with small banks. Next, we use intangible assets to measure banks' fintech investments. Interestingly, our results show that the impacts of fintech investment are significantly positive for small banks, while the impacts of fintech investment are negative but not significantly for large banks.

Second, in terms of deposit efficiency, P2P lending has negative impacts on both large and small banks' scale efficiency (TE) and managerial efficiency (PTE) in deposits. The impacts on large banks' managerial loan efficiency (positive) is contrary to the impacts on large banks' managerial deposit efficiency (negative) Next, we also show that the impacts of fintech investment are significantly positive for small banks, but the impacts of fintech investment are not significant for large banks.

Finally, the impacts on the UK banks are positive but not significantly in both OLS and panel data with fixed effect models. This indicates that P2P lending has negative but not significant impacts on bank performance. A possible explanation is that since Zopa operates as a match maker, so compared to LendingClub in the US, its competition impacts on the traditional banks are less severe and hence the effects are not significant. The coefficients of fintech investments are all significantly positive, showing that UK banks are well prepared for competition from P2P lending.

1.1 Related Literature

Most P2P lending literature focuses on aspects such as loan, interest rate, and credit risk on banks. From De Roure, Pelizzon, Thakor (2018), the purpose of this paper is to examine how P2P lenders and banks compete for borrowers. According to their empirical results, they show that P2P lending increases and total bank lending declines when some banks face higher regulatory costs in Germany. Moreover, they also find that P2P borrowers are risker and less profitable than bank borrowers. Thus, the conclusion is that the advent of P2P lending may cause the banking sector to shrink, but also to be less risky and possible more profitable in terms of risk-adjusted returns on assets. However, from Tang (2018), he thinks that the credit expansion opportunities brought by P2P lenders are likely to occur only for infra-marginal bank borrowers. On the other hand, P2P platforms complement banks by focusing on the market segment for small loans. The amount requested by borrowers migrating from banks to P2P platforms is larger than 90% of pre-existing P2P loans.

From Wolfe and Yoo (2018), because they want to know whether P2P and banks have competition on interest rate, they make a survey on average bank issue loans. The result shows that although banks do not respond to P2P by changing loan interest rates, their issues loans at rates approximately 164 BPs higher than a P2P company called Prosper. That is, compared to traditional banks, P2P have interest rate advantage on borrowers.

Finally, from Yan, Yu and Zhao (2015), they use information economics perspective to investigate how information signaling and search costs affect information asymmetry in the lending business and analyze how big data reduces information asymmetry in P2P lending. P2P are using a wide range of data to evaluate credit risk, while traditional banks may not have the technical ability or analytical skills to utilize these new forms of data. From Serrano-Cinca and Gutierrez-Nieto (2016), they use LendingClub data to test which credit scoring system is better in P2P lending and traditional banks. Their result shows that P2P lending is not currently a fully efficient market. This means that data mining techniques are able to identify the most profitable loans, or in financial jargon, "beat the market". That is, a credit investigation system used in P2P outperforms the result of the system in traditional banks. However, there is also different opinions on this issue. From Kafer (2016), he concludes that P2P lending is more risky than

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traditional banking. In the past, information asymmetry is a problem in traditional banks, and the development of P2P lending cannot solve the problem. The most critical reason is that borrowers may offer wrong information, and lenders cannot investigate borrowers' credit like what banks do in usual. Thus, high amount of loans on P2P platforms is more risky than traditional banks. Finally, from Emekter, Tu, Jirasakuldech (2014), they find that P2P lending could offer certain benefits to both borrowers and lenders. But for the credit issue, loans with lower credit grade and longer duration are associated with high mortality rate, and higher interest rates charged on the high-risk borrowers are not enough to compensate for higher probability of the loan default. That is, compared to traditional banks, lenders take risks themselves when they invest on P2P platforms.

Other than what issue discussed from above, default risk of P2P platforms is also an aspect that we should focus. Yoon, Yi and Feng (2018) use Chinese online P2P lending data to show that sever competition among platforms can increase risky behaviors of platforms by allowing risker borrowers into the system. In addition, they find that platforms can default as a result of lending environments and other macro environment such as stock market condition or increase in speculative opportunities play important roles to increase the platform default rate. They use platform default risk as a dependent variable which is defined as the risk that platforms may incur through default events, such as running away with money and termination of business. As for independent variables they use completion, average rate of return, third-party guarantee, etc.

Online P2P lending has gained scientific relevance over the past years. The availability of data about markets and transactions allows researchers from different disciplines to investigate the various determinants that play a role in the process of funding Bachmann et al (2011).

Peer-to-peer (P2P) lending platforms provide credits without bank intermediation where individuals and companies invest in small business. Those platforms match borrowers and lenders directly. From a modest base, P2P lending is growing fast in the U.S. and UK (Vives, 2017). There are two different business models. One is that the lender puts money in a pool of funds. The P2P lending company dispatches the money to different borrowers, and the other one is that it just offers a platform that borrowers and lenders can make a deal directly on the

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platform (Wang, Chen and Song, 2015). Two different business models may lead to different impacts on banking system.

As for the impact of fintech on banks, the main developments in the application of digital technology have occurred so far in lending, payment systems, financial advising, and insurance. In all those segments of business fintech has the potential to lower the cost of intermediation and broaden the access to finance increasing financial inclusion. One of the reasons for this efficiency-enhancing role lies in the potential to help overcome information asymmetries, which are at the root of the banking business (Vives, 2017). However, other than the positive impacts, there are also negative impacts of fintech on banks. For example, payment services. Start-up services providers, search engines, and social networks have expand their services "interfering" in the fields traditionally covered by banks (Romanova and Kudinska, 2016). Hence, the relationship between fintech and banks is not only cooperative, but also competitive. According to Milne and Parboteeah (2016), P2P lending is fundamentally complementary to and not competitive with conventional banking. Their argument is based on the fundamental core of most bank business model is the provision of liquidity service. Synergies in liquidity explain the co-existence of loan, deposit and payment services in banks. they therefore expect banks to adapt to the emergence of P2P lending, either by cooperating closely with third-party P2P lending platforms or offering their own proprietary platforms to serve their existing customers.

Bank efficiency is a huge issue discussed by a lot of literature. Some use cost to income ratio to measure bank efficiency such as Bautista, Sanchez and Sobrino (2013), and Li et al (2001). For example, Bautista, Sanchez and Sobrino (2013) use all staff costs and other general operating expense including depreciation costs as their numerator of the cost to income ratio. Then, net interest income, commissions derived from baking intermediation activities, and other income form activities unrelated to banking intermediation are taken as denominator of the cost to income ratio. Some others would like to use DEA model to calculate efficiency scores as an indicator. DEA analysis in banks are well-studied, so we refer to some reviewing papers such as Yue (1992), Eshlaghy, Shafiee, Saleh and Hosseinzadeh (2011), and Fethi and Pasiouras (2009) choose what variables shall be used in our models. For example, Yue (1992) uses interest expense, non-interest expense, transaction deposit, and non- transaction deposit as input variables;

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interest income, non-interest income and total loans as output variables to measure bank efficiency. Moreover, Eshlaghy, Shafiee, Saleh and Hosseinzadeh (2015), they use two-stage DEA model to measure bank branch performance in Iran. The performance is a combination of profitability efficiency and effectiveness, so they use two-stage evaluation process to separate profitability and effectiveness. In the first stage model, they choose personal expense, equipment expense, and operational expense as input variables. As for output variables, they choose non-operational income, sum of deposit, and commission. In the second stage, they use the first stage outputs as their input variables. That is, non-operational income, sum of deposit, and commission are input variables in the second stage model to measure effectiveness of bank branch performance. Then, they use net income as their output variable in the second stage model. Finally, according to their result, they show that the importance of profitability efficiency and effectiveness in the overall performance in bank branches in Iran.

Finally, there are a lot of literature discuss which factors affect bank efficiency. According to Bautista, Sanchez and Sobrino (2013), they conclude three relevant aspects related to the determinants of bank efficiency in terms of bank size, diversification and funding structure in EU. First, they find that the efficiency ratio generally has a positive relationship with bank size. Second, their result show that diversification is one of the strongest explanatory variables in the efficiency ratio. That is, if a bank has higher other income, its efficiency is better. Third, there is no link between higher capital requirements for banks and efficiency levels.

The remainder of the paper is organized as follows. Section 2 first presents our analytical model. We first derive banks' payoff and efficiency ratio before the development of P2P. Then after P2P lending showing up, the business of banks have been changed. Deposit in banks has one more option to inflow, and cost of banks will reduce due to a decrease in credit investigation. Thus, under different impacts of P2P on banks, we show that there are three different situations on the change of bank efficiency. Section 3 provides the empirical study and result for our model. We compare the impacts of P2P in the U.S. and UK. Section 4 concludes the paper with policy implication. The appendix contains a brief review on the theoretical background for efficiency scores, and reasons for the input and output variables used in calculating the efficiency scores.

2. Analytical model

Here we first describe a bank's profit and efficiency measure without the presence of P2P lending. This helps us identify the determinants that affect the banking profit and efficiency. Then we demonstrate how the presence of P2P lending will affect a bank's performances.

2.1 Without P2P Lending

We assume that after receiving customers' deposits, each bank will make a portfolio choice between risky, safe assets and making loans. First, let D_i^0 be the received deposit, and I_i be bank *i*'s investment in risky assets whose rate of return *R* is random and follows a distribution *F(R)*. The expected return from risky investment is hence $\int\{(1+R)I_i\}dF(R)$.

Next, let L_i be the total sum of loans made to its customers. Let $\overline{P}$ be the perceived repayment rate, and ϕ is the rate of return from this loan. The expected return from risky investment is hence $\overline{P}(1+\phi)L_i$.

We normalize the rate of return for safe asset to be zero and hence the total return from safe asset is $(D_i^0 - I_i - L_i)$. Finally, we assume that there is a convex cost function for managing the deposit: $c(D_i^0)$. Overall, bank i's profit is given by

$$\pi_i = \int\{(1+R)I_i\}dF(R) + \overline{P}(1+\phi)L_i + (D_i^0 - I_i - L_i) - c(D_i^0).$$

where the first term describes the expected return from risky investment, the second term indicates the expected return from making loans to customers, and the third term is the total return for safe asset.

Following Li et al. (2001), Marcus(2001), Forster and Shaffer (2005), and Liebscher (2005), we consider the following bank efficiency ratio, which is defined as the ratio of 'non-interest expenses divided by revenue', that is,

$$c_i(D_i^0)/\{\int(1+R)I_i dF(R) + \overline{P}(1+\phi)L_i + (D_i^0 - I_i - L_i)\}. \tag{1}$$

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As π_i increases, this ratio will decrease and the bank efficiency will increase. Likewise, as D_i^0 increases, if the marginal cost $c'(D_i^0)$ is relatively small, then the bank efficiency will increase.

2.2 With P2P Lending

P2P lending can affect a bank's profit and efficiency in three aspects. First, since P2P platforms normally offer higher returns, some depositors will move their money to P2P platforms. Let O_i indicate the deposit outflow of bank i, and hence the received deposit becomes $D_i^0 - O_i$.

Second, P2P platforms also provide a new investment revenue for each bank. Let L_i^p indicate the amount of money that a bank invests in P2P lending, and let $r > 0$ be the rate of return from P2P lending. Despite of the higher returns, there are two types of default risks in P2P lending. That is, in addition to the risk that the borrowers can default, there is also a risk that a P2P platform can default. According to financial news, on May 24, 2019, one of UK P2P companies called Lendy announced that it has entered voluntary administration. Hundreds of investors have joined the Lendy Action Group which aims to act as a point of coordination, work collectively to recover fund, be a voice to the administrators, regulators and press and to consider further opportunities such as legal action. Thus, the risk of P2P platform default cannot be ignored. Therefore, we use $0 < \alpha < 1$ to summarize the probability of defaults from P2P lending. Hence the expected return for investing in P2P lending is $(1-\alpha)(1+r)L_i^p$.

Third, since some risky or low-income customers have turned to P2P for funding, we assume that there can be a decrease in credit investigation cost. Let $\bar{c}$ be the reduced cost function for managing deposit, and by assumption, we have $\bar{c}(.) < c(.)$. Hence in the presence of P2P lending, the overall non-interest expense becomes $\bar{c}(D_i^0 - O_i)$.

Since the investment decisions could change with the presence of P2P lending, let I'_i and L'_i denote the new investment in risk asset and making loans, with $I_i^{'} \le I_i$ and $L_i^{'} \le L_i$. Overall, bank i's profit is given by

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$\pi_i^p = \int (1+R)I_i^{'}dF(R) + \overline{P}(1+\phi)L_i^{'} + (1-\alpha)(1+r)L_i^p + (D_i^0 - O_i - I_i^{'} - L_i^{'} - L_i^p) - \overline{c}(D_i^0 - O_i)$ .Then, the bank efficiency ratio will also change. That is,

$$\overline{c}(D_i^0 - O_i) / \{\int (1+R)I_i^{'}dF(R) + \overline{P}(1+\phi)L_i^{'} + (1-\alpha)(1+r)L_i^p + (D_i^0 - O_i - I_i^{'} - L_i^{'} - L_i^p)\} . \quad (2)$$

Comparing equation (1) and (2), we can make the following conclusions for the effects of P2P lending on bank's efficiency. First, in the numerator, since some risky or low-income customers have turned to P2P platforms for funding, the decrease in credit investigation cost has caused a cost saving. Together with smaller amount of deposit, the overall non-interest expense will be smaller. *Ceteris paribus*, the bank efficiency will increase.

Second, in the denominator, the deposit loss has a direct negative impact, and it also has further indirect impacts on the amount of risky investment and loans. If the cost saving is sufficiently small, the bank efficiency will decrease.

Finally, although the rate of return could be higher than safe asset and ordinary loans, the default risk α from P2P lending will have a negative impact on the bank efficiency.

3. Empirical Studies

This section investigates the effects of P2P lending on bank performance. As described in the analytical model, P2P lending can affect bank performance from three aspects. (1) Since some risky or low-income customers have turned to P2P platforms for funding, the decrease in credit investigation cost has caused a cost saving and the bank performance will increase. (2) Since part of depositors switch to P2P lending, there is a direct negative impact from deposit loss, It also has further indirect impacts on the amount of risky investment and loans. If the cost saving is sufficiently small, the bank efficiency will decrease. (3) Although the rate of return could be higher than safe asset and ordinary loans, the default risk from P2P lending will have a negative impact on the bank efficiency.

There are mainly two types of business models in P2P platforms. First, the P2P company serves as a dealer; Lenders deposits their money in a pool of fund, and the P2P company dispatches the money to different borrowers. In this model, lenders don't know the borrowers'

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information. The largest P2P company in the U.S., LendingClub, provides an influential example for the first model. Second, the P2P company serves as a match maker; It offers a platform for borrowers and lenders to match and make a deal directly and the platform only charges small membership and transaction fees. In this model, lenders can observe borrowers' information (Wang, Chen and Song, 2015). The largest P2P company in U.K., Zopa, provides an influential example for the second framework.

The intermediary role of P2P company in the first framework is similar to traditional banks. Therefore, in addition to the three aspects of influences on bank performance mentioned above, there can be a further negative impact from more competition in the first model. To justify this hypothesis, we study the effects of P2P lending on bank efficiency and performance for both US and UK.

Moreover, due to data unavailability, we use different proxies for bank performance in the US and UK. First, for the US, we follow most literature and apply the widely used input-oriented non-parametric Data Envelopment Analysis (DEA) to calculate the efficient frontier and efficiency scores. Second, for the UK, since there is no available data for several variables used to calculate the efficiency scores, we use the ratio of revenue divided by total assets as a proxy of bank performance in the UK.

We evaluate the impacts of P2P on bank performance by using two-stage approach. In the first-stage, we calculate bank performance for the US and UK. Then in the second-stage, we regress bank performance on a firm-specific proxy for P2P lending while controlling for firm specific characteristics.

The regression models for the US and UK are a bit different due to different measures on the dependent variable. First, for the US, we run both Tobit and OLS models to estimate linear relationships between bank performance and the P2P lending variable. As the efficiency scores cover from zero to one, the Tobit or logistic model is the most often used model in the literature. Hoff (2007) compared the Papke--Wooldridge approach and the unit-inflated beta model to Tobit model for the second stage regressions and concludes that the Tobit approach in most cases is sufficient in representing the second stage regression model. However, according to Hoff (2007), OLS may in cases replace Tobit as a sufficient second stage DEA model. Second, for

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the UK, we run both OLS and panel data with random effect models to estimate linear relationships between bank performances and the P2P lending variable.

3.1 Data and Variables

First, our data for the U.S. banks is extracted from the website of Federal Deposit Insurance Corporation (FDIC). To examine whether the effects of P2P lending change with the banking scale, we follow Wolfe and Yoo (2018) in classifying banks with total assets greater than US$300 million as "large banks" and those with total assets under US$300 million as "small banks". Our sample covers 20 large banks and 20 small banks from 2000 to 2015 in the U.S. As for the UK banks, due to data unavailability, we collect our data from the websites of 6 major banks in the UK (HSBS, Barclays, Standard Chartered, Lloyds, Santander UK, and RBS) (Drake, 2001) from 2005 to 2015.

Second, for P2P lending transaction data, we download it from the websites of LendingClub in the US and Zopa in the UK.

3.1.1 Performance Variables

Due to data unavailability, we use different proxies for bank performance in the US and UK. First, in the Appendix, we briefly overview the theoretical background for the efficiency scores, and reasons for the input and output variables used in calculating the efficiency scores. Then we use Coelli.s (1996) Data Envelopment Analysis Computer Program (DEAP) version 2.1 to calculate the efficiency scores. As described in the analytical model, P2P lending will affect commercial banks' loans and deposits. To distinguish the two aspects of effects, we use two groups of output variables in calculating the efficiency scores, i.e.,

Model 1: Input: employees, total fixed assets, and total interest expense
Output: **loans**, and total interest income
Model 2: Input: employees, total fixed assets, and total interest expense.
Output: **deposits**, and total interest income)

Model 1 and 2 are only different in the choice of output variables. Model 1 describes the efficiency on loans and Model 2 describes the efficiency on deposits. For each model, we

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calculate the technical efficiency scores (TE).and the pure technical efficiency scores (PTE) (see Charnes et al., 1978; Banker et al., 1984). We want to identify the sources of efficiency changes in the banking system with emphasis on whether this is a result of scale change (TE) or managerial underperformance (PTE).

Moreover, to examine whether the effects of P2P lending change with the banking scale, we follow Wolfe and Yoo (2018) in classifying banks with total assets greater than US$300 million as "large banks" and those with total assets under US$300 million as "small banks". Table A6~A9 present the efficiency scores for large and small banks using model 1 and 2.

Second, for the UK, since there is no available data for several variables used to calculate the efficiency scores, we use "net income" as a proxy of bank performance in the UK.

3.1.2 The Firm-Specific Proxy for P2P lending

The P2P lending industry started in February 2005 when the first P2P lending company, Zopa, was founded in the UK. In the US, P2P lending started in February 2006 with the launch of Prosper Marketplace, followed by LendingClub. A turning point in the recent history of P2P lending was the bankruptcy of Lehman Brothers in 2008. As people lost confidence in financial institutions and were no longer able to secure credit at a reasonable level of interest – P2P lending emerged as a viable alternative.[3] The industry has been growing rapidly and currently, the largest markets are China, the United States and Europe. Across the world, there are thousands of platforms that have distributed billions worth of loans.

Since P2P lending operates online, it has impacts on the entire banking system. We can collect transaction data for the two P2P lending companies, but there is no detailed location information of the lenders and borrowers to describe the potential firm-specific impacts. Also, a dummy variable indicating when P2P lending started cannot be used to measure its impact on individual banks, because it is difficult to isolate the impacts from the financial turmoil in 2008 and P2P lending.

Hence, to find a firm-specific proxy for p2p lending, we compare the annual lending

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3 http://peersociallending.com/news/history-peer-peer-lending/

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volume of the P2P platform with every item in the income statements of the whole commercial banks. According to their similarity in time paths and the correlation coefficient, we choose "small time deposits" which are time deposits less than $100,000 in commercial banks as our firm-specific proxy for P2P lending effect in both UK and US. [4] Specifically, Figure 1 shows the patterns of the annual lending volume of LendingClub and the levels of small time deposits of commercial banks in the U.S. After 2008, when P2P lending volume gradually ascended, the small time deposits in U.S. commercial banks gradually declined. The correlation between the two terms is -0.745, which indicates that P2P lending volume (LendingClub) is highly and negatively correlated with small time deposits of commercial banks in the U.S.

As for the UK data, due to data unavailability, we have collected data from the websites of six major banks (HSBS, Barclays, Standard Chartered, Lloyds, Santander UK, and RBS). We compare the annual lending volume of Zopa with the total amount for every item in the income statements of six sample banks. Figure 2 shows the patterns of Zopa's annual lending volume and the sum of small time deposits of six sample banks. Although the small time deposits still increased after 2008, the increasing rate slowed down and even became negative after 2012. The correlation between the two terms is -0.421, which indicates that P2P lending (Zopa) lending volume is negatively correlated with the total sum of small time deposits of our six commercial banks in the U.K

[4] We have tried to use "*P2P lending volume** bank i's small time deposit " and "*P2P lending volume** ($\frac{\textit{bank i's small time deposit}}{\textit{sample sum of small time deposits}}$) " as our firm-specific proxy for P2P lending. The results show that these proxy variables are significant at significant level α=1% for large banks; but not significant for small banks. Hence, we will present only the empirical results using small time deposits as the firm-specific proxy for P2P lending.

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Figure 1 P2P Lending and Small Time Deposits in the U.S

P2P annual lending data is from the website of Lending Club (largest P2P company in the U.S). Small time deposits are time deposits less than $100,000 in commercial banks. The correlation between P2P lending and small time deposits is -0.745, which indicates that P2P lending is highly and negatively correlated with small time deposits. The unit of P2P lending and small time deposits are millions USD.

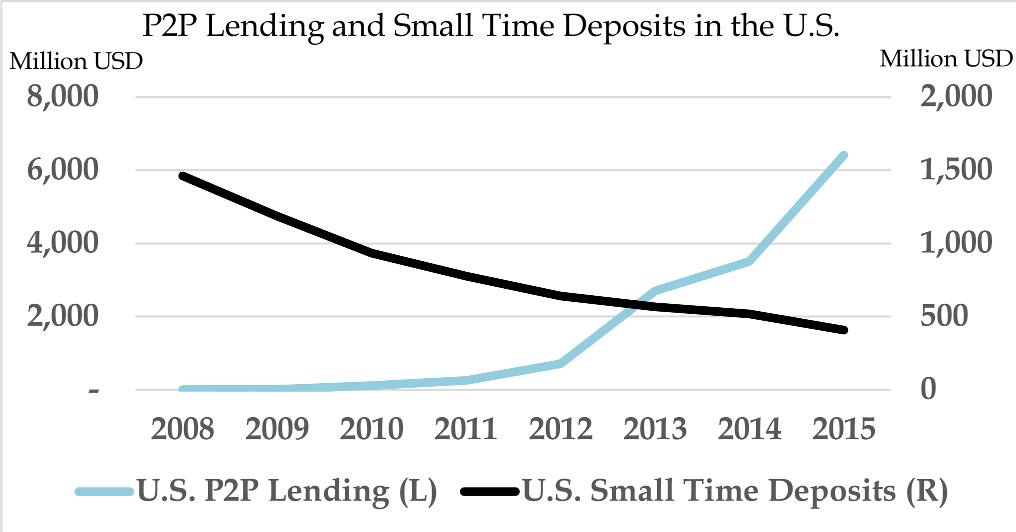
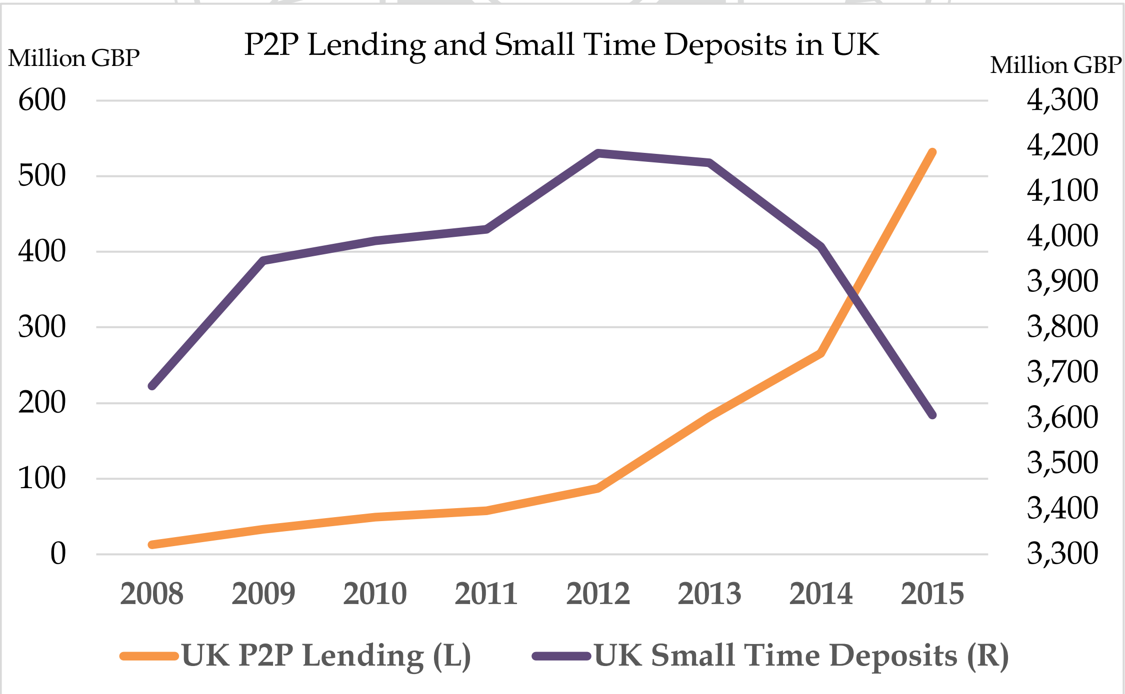


Figure 2 P2P Lending and Small Time Deposits in UK

P2P annual lending data is extracted from the website of Zopa (the largest P2P company in UK). Small time deposits are time deposits less than $100,000. Since the small time deposits data for all banks in UK is not available, we collect data from the websites of 6 major banks in UK (HSBS, Barclays, Standard Chartered, Lloyds, Santander UK, and RBS) (Drake, 2001). We find that the correlation between P2P lending and small time deposits of the UK is -0.421. The unit of P2P lending and small time deposits are millions GBP.



3.1.3 Control Variables

Following the literature, we use the following control variables to describe firm specific characteristics.

LnTA: Total asset (TA) is used to measure the scale of a bank in the bank efficiency literature. According to Andries (2011), bank size (total assets) and technical efficiency are positively related. In this paper, we take the nature log of bank's total assets (LnTA) as our control variable.

CR: Total capital ratio defined as, CR= (E_i / TA_i)*100, where E_i is bank i's equity. CR represents the degree of financial independence. Higher capital ratios have a positive effect on efficiency levels (Fiordelisi al., 2011).

ROA: Return on assets is the net income divided by total assets. ROA is usually used as a measurement of a bank profitability and hence positvely related to bank efficiency (Mathuva, 2009).

IA: Intangible assets of a bank. "*Intangible assets are assets that do not have a physical or financial embodiment. Termed 'intellectual assets' in previous OECD work, intangible assets have also been referred to as knowledge assets or intellectual capital. Much of the focus on intangibles has been on R&D, key personnel and software. But the range of intangible assets is considerably broader. One classification groups intangibles into three types: computerized information (such as software and databases); innovative property (such as scientific and nonscientific R&D, copyrights, designs, trademarks); and economic competencies (including brand equity, firm-specific human capital, networks joining people and institutions, organizational know-how that increases enterprise efficiency, and aspects of advertising and marketing)*".[5] Hence, as the intangible assets increase, bank efficiency will increase.

LC: Labor cost of a bank. Mester (1996) and Das (2009) used the number of employees as an

[5] https://www.oecd.org/sti/inno/46349020.pdf

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input variable to calculate the efficiency scores. Due to data unavailability, we use labor cost as proxy for the numbers of workers. However, its effects on bank performance are controversial, as higher labor cost can indicate higher average wage or more employees, which will lead to different effects on firm efficiency.

Table 1 Variables and Definitions

Variable	Definition	Refrence
LnTD	Nature log of small time deposits, which are deposits less than $100,000 in a bank.	N/A
LnTA	Nature log of total assets of a bank	Andries (2011)
CR	Total capital ratio = (Equity/Total asset)*100	(Fiordelisi al., 2011)
ROA	Return on asset = Net income/Total asset	(Mathuva, 2009)
IA	Intangible asset of a bank	OECD
LC	Labor cost of a bank	Mester (1996) and Das (2009)

Table 2 Summary of Statistics for Explanatory Variables for large banks

The table presents the summary statistics for variables used for regression models. According to Wolfe and Yoo (2018), large banks have total assets greater than $300 million. Intangible asset (IA) is in million USD.

Variable	Mean	St.Dev.	Min	Max
LnTD	6.95	0.46	5.24	7.49
LnTA	8.43	0.45	7.88	9.32
CR(%)	11.82	0.03	6.81	18.97
ROA(%)	0.94	0.003	0.49	1.61
IA	13,406	14,917	534	61,219

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Table 3 Summary of Statistics for Explanatory Variables for small banks

The table presents the summary statistics for variables used for regression models. By Wolfe and Yoo (2018), small banks have total assets smaller than $300 million. Intangible asset (IA) is in million USD.

Variable	Mean	St.Dev.	Min	Max
LnTD	5.40	0.09	5.19	5.5
LnTA	4.51	0.26	4.12	4.99
CR(%)	11.70	3.60	7.05	21.82
ROA(%)	1.09	0.68	0.12	2.73
IA	209	503	0	1,650

Table 4 Summary of Statistics for Explanatory Variables in UK

The table presents the summary statistics of variables for the regression models. Since the data for all banks in UK is not available, we collect data from the websites of 6 major banks in UK (HSBS, Barclays, Standard Chartered, Lloyds, Santander UK, and RBS) (Drake, 2001). Intangible asset (IA) and labor cost (LC) are measured in million GBP.

Variable	Mean	St.Dev.	Min	Max
LnTD	5.69	0.29	5.25	6.17
LnTA	5.92	0.30	5.45	6.38
CR(%)	6.61	1.08	5.52	8.20
IA	7,037	8,233	2,231	16,738
LC	7,022	4,316	1,115	13,537

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3.2 Empirical Results

We regress the performance variable (efficiency scores, net income) on firm-specific proxy for P2P lending while controlling other firm characteristics. We use Eviews 8 and Stata 15 to estimate the coefficients in the Tobit and OLS regressions.

3.2.1 Efficiency

As described, to distinguish the two aspects of effects from P2P lending, we use Model 1 to describe the efficiency on loans and Model 2 to describe the efficiency on deposits. Table A6~A9 present the two efficiency scores (TE and PTE) in the US for four categories: large-model 1, small-model 1, large-model 2 and small-model 2. We indicate the efficiency scores in the four categories as: $EfficiencyL1$, $EfficiencyS1$, $EfficiencyL2$, $EfficiencyS2$. According to Mester (1996), Das (2009), Mathuva (2009), Fiordelisi al. (2011) and Andries (2011), we will run the following four regression models for TE and PTE under different assumptions on technology (i.e., CRS and VRS). We want to identify the sources of efficiency changes in the banking system with emphasis on whether this is a result of scale changes (TE) or managerial underperformance (PTE).

$$\text{Efficiency L1}_{\text{it}} = \beta_0 + \beta_1 \text{LnTD}_{\text{it}} + \beta_2 LnTA_{it} + \beta_3 CR_{it} + \beta_4 ROA_{it} + \beta_5 IA_{it} + \varepsilon_{\text{it}}, \qquad (3)$$

$$\text{Efficiency S1}_{\text{it}} = \beta_0 + \beta_1 \text{LnTD}_{\text{it}} + \beta_2 LnTA_{it} + \beta_3 CR_{it} + \beta_4 ROA_{it} + \beta_5 IA_{it} + \varepsilon_{\text{it}}, \qquad (4)$$

$$\text{Efficiency L2}_{\text{it}} = \beta_0 + \beta_1 \text{LnTD}_{\text{it}} + \beta_2 LnTA_{it} + \beta_3 CR_{it} + \beta_4 ROA_{it} + \beta_5 IA_{it} + \varepsilon_{\text{it}}, \qquad (5)$$

$$\text{Efficiency S2}_{\text{it}} = \beta_0 + \beta_1 \text{LnTD}_{\text{it}} + \beta_2 LnTA_{it} + \beta_3 CR_{it} + \beta_4 ROA_{it} + \beta_5 IA_{it} + \varepsilon_{\text{it}}. \qquad (6)$$

The only difference between model 1 and model 2 is on the choice of output variables in calculating the efficiency scores. Model 1 measures the efficiency of banks' lending performance, and model 2 measures the efficiency of banks' deposit performance. The regression results for equations (3), (4), (5), and (6) are presented in Table 5, 6, 7 and 8, respectively.

Recall that our firm-specific proxy for P2P lending is LnTD, and the directions of their impacts on bank performance should be reversed. We can address the effects of P2P lending from various aspects.

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Table 5 P2P lending and bank efficiency for large banks in the US (Model 1)

This table presents the regression results for the impact of LnTD on two efficiency scores: TE (technical efficiency) and PTE (pure technical efficiency) on large banks. Large banks are those total assets smaller than $300 million. The regression model is

$$EfficiencyL1_{it} = \beta_0 + \beta_1 LnTD_{it} + \beta_2 LnTA_{it} + \beta_3 CR_{it} + \beta_4 ROA_{it} + \beta_5 IA_{it} + \varepsilon_{it}$$

We take both TE and PTE as dependent variables to order to compare the impacts under different assumptions on technology (i.e., CRS and VRS). $LnTD_{it}$ is the proxy for P2P lending. We use four control variables (total assets, capital ratio, return on assets and intangible assets) to indicate the overall or core business performance of banks. Model 1 and Model 2 are different in the output variables used to calculate the efficiency scores. *, **, and *** measure the significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable **TE**	Tobit Model (N=320)		OLS (N=320)	
	Coefficient Estimate	P>|t|	Coefficient Estimate	P>|t|
Intercept	1.001 **	0.023	0.816 **	0.019
LnTD	0.029 *	0.075	0.030 **	0.022
LnTA	- 0.040	0.109	- 0.032	0.108
CR	0.402	0.176	0.401 *	0.090
ROA	4.189 **	0.045	3.186 **	0.050
IA	- 0.001	0.463	- 0.002	0.288
Pseudo/Adj R^2	0.056		0.037	
R^2 / F	N/A		0.052/ 3.451	
Dependent Variable **PTE**	Tobit Model (N=320)		OLS (N=320)	
	Coefficient Estimate	P>|t|	Coefficient Estimate	P>|t|
Intercept	1.303 **	0.015	1.054 ***	0.001
LnTD	- 0.036 *	0.070	- 0.021 *	0.057
LnTA	0.013	0.671	0.008	0.654
CR	- 0.103	0.776	- 0.006	0.977
ROA	0.874	0.717	0.030	0.983
IA	- 0.001	0.556	- 0.002	0.389
Pseudo/Adj R^2	0.022		0.067	
R^2 / F	N/A		0.026/ 1.700	

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Table 6: P2P lending and bank efficiency for small banks in the US (Model 1)

This table presents the regression results for the impact of LnTD on two efficiency scores: TE (technical efficiency) and PTE (pure technical efficiency) on small banks. Small banks are those total assets smaller than $300 million. The regression model is

$$EfficiencyS1_{it} = \beta_0 + \beta_1 LnTD_{it} + \beta_2 LnTA_{it} + \beta_3 CR_{it} + \beta_4 ROA_{it} + \beta_5 IA_{it} + \varepsilon_{it}$$

We take both TE and PTE as dependent variables to order to compare the impacts under different assumptions on technology (i.e., CRS and VRS). $LnTD_{it}$ is the proxy for P2P lending. We use four control variables (total assets, capital ratio, return on assets and intangible assets) to indicate the overall or core business performance of banks. Model 1 and Model 2 are different in the output variables used to calculate the efficiency scores. *, **, and *** measure the significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable **TE**	Tobit Model (N=320)		OLS (N=320)	
	Coefficient Estimate	P>|t|	Coefficient Estimate	P>|t|
Intercept	2.942 ***	0.000	1.801 ***	0.000
LnTD	0.084 ***	0.000	0.031 ***	0.010
LnTA	- 0.231 ***	0.000	- 0.098 ***	0.000
CR	- 0.813 ***	0.002	- 0.429 ***	0.003
ROA	0.355	0.797	- 0.614	0.440
IA	0.000 ***	0.009	0.045 **	0.029
Pseudo/Adj R^2	0.258		0.091	
R^2 / F	N/A		0.105/ 7.351	
Dependent Variable **PTE**	Tobit Model (N=320)		OLS (N=320)	
	Coefficient Estimate	P>|t|	Coefficient Estimate	P>|t|
Intercept	2.961 ***	0.000	1.618 ***	0.000
LnTD	0.063 **	0.021	0.017	0.174
LnTA	- 0.206 ***	0.000	- 0.069 ***	0.007
CR	- 0.770 ***	0.020	- 0.417 ***	0.005
ROA	- 3.928 *	0.064	- 1.410 *	0.083
IA	0.093**	0.048	0.039 *	0.060
Pseudo/Adj R^2	0.133		0.066	
R^2 / F	N/A		0.081/ 5.506	

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Table 7 P2P lending and bank efficiency for large banks in the US (Model 2)

This table presents the regression results for the impact of LnTD on two efficiency scores: TE (technical efficiency) and PTE (pure technical efficiency) on large banks. Large banks are those total assets smaller than $300 million. The regression model is

$$EfficiencyL2_{it} = \beta_0 + \beta_1 LnTD_{it} + \beta_2 LnTA_{it} + \beta_3 CR_{it} + \beta_4 ROA_{it} + \beta_5 IA_{it} + \varepsilon_{it}$$

We take both TE and PTE as dependent variables to order to compare the impacts under different assumptions on technology (i.e., CRS and VRS). $LnTD_{it}$ is the proxy for P2P lending. We use four control variables (total assets, capital ratio, return on assets and intangible assets) to indicate the overall or core business performance of banks. Model 1 and Model 2 are different in the output variables used to calculate the efficiency scores. *, **, and *** measure the significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable **TE**	Tobit Model (N=320)		OLS (N=320)	
	Coefficient Estimate	P>|t|	Coefficient Estimate	P>|t|
Intercept	0.905	0.058	2.078 ***	0.000
LnTD	0.033	0.058	0.033 **	0.039
LnTA	- 0.029	0.278	- 0.102 ***	0.000
CR	- 1.187	0.000	- 0.678 **	0.022
ROA	2.740	0.225	6.851 ***	0.001
IA	0.001	0.532	0.003	0.119
Pseudo/Adj R^2	0.076		0.093	
R^2 / F	N/A		0.108/ 7.568	
Dependent Variable **PTE**	Tobit Model (N=320)		OLS (N=320)	
	Coefficient Estimate	P>|t|	Coefficient Estimate	P>|t|
Intercept	0.889 **	0.045	1.777 ***	0.000
LnTD	0.029 *	0.068	0.029 **	0.020
LnTA	- 0.018	0.464	- 0.076 ***	0.000
CR	- 0.878 ***	0.003	- 0.046	0.844
ROA	2.820	0.168	2.627	0.102
IA	- $4.68*10^{-4}$	0.814	- $2,94*10^{-5}$	0.985
Pseudo/Adj R^2	0.063		0.086	
R^2 / F	N/A		0.100/ 7.006	

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Table 8 P2P lending and bank efficiency for small banks in US (Model 2)

This table presents the regression results for the impact of LnTD on two efficiency scores: TE (technical efficiency) and PTE (pure technical efficiency) on small banks. Small banks are those total assets smaller than $300 million. The regression model is

$$EfficiencyS2_{it} = \beta_0 + \beta_1 LnTD_{it} + \beta_2 LnTA_{it} + \beta_3 CR_{it} + \beta_4 ROA_{it} + \beta_5 IA_{it} + \varepsilon_{it}$$

We take both TE and PTE as dependent variables to order to compare the impacts under different assumptions on technology (i.e., CRS and VRS). $LnTD_{it}$ is the proxy for P2P lending. We use four control variables (total assets, capital ratio, return on assets and intangible assets) to indicate the overall or core business performance of banks. Model 1 and Model 2 are different in the output variables used to calculate the efficiency scores. *, **, and *** measure the significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable **TE**	Tobit Model (N=320)		OLS (N=320)	
	Coefficient Estimate	P>|t|	Coefficient Estimate	P>|t|
Intercept	2.715 ***	0.000	2.093 ***	0.000
LnTD	0.058 **	0.016	0.035 **	0.030
LnTA	- 0.199 ***	0.000	- 0.134 ***	0.000
CR	- 0.806 ***	0.006	- 0.545 ***	0.006
ROA	3.146 **	0.041	2.689 **	0.014
IA	0.00014 ***	0.001	0.0791 ***	0.005
Pseudo/Adj R^2	0.185		0.090	
R^2 / F	N/A		0.105/ 7.346	

Dependent Variable **PTE**	Tobit Model (N=320)		OLS (N=320)	
	Coefficient Estimate	P>|t|	Coefficient Estimate	P>|t|
Intercept	3.686 ***	0.000	2.239 ***	0.000
LnTD	0.116 ***	0.000	0.051 ***	0.000
LnTA	- 0.322 ***	0.000	- 0.154 ***	0.000
CR	- 0.954 ***	0.001	- 0.500 ***	0.003
ROA	2.072	0.164	0.800	0.381
IA	0.011 ***	0.009	0.050 **	0.031
Pseudo/Adj R^2	0.327		0.135	
R^2 / F	N/A		0.145/ 10.661	

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(i) Loan Efficiency (model 1)

First, Table 6 shows that the coefficients of LnTD are both positive and most significantly for both TE and PTE in small banks. This indicates that P2P lending has negative impacts on small banks' scale efficiency (TE) and managerial efficiency (PTE) in loans. Differently, Table 5 shows that the coefficient of LnTD is significantly positive for TE, but significantly negative for PTE. This indicates that P2P lending has a negative impact on large banks' scale efficiency (TE) but a positive impact on large banks' managerial efficiency (PTE).

Since P2P lending offers quick loans with lower interests. After the financial turmoil in 2008, people lost confidence in financial institutions, so P2P lending emerged as a viable alternative. Both large and small banks have lost their amount of customers (i.e. TE), but the large banks' managerial efficiency has increased with P2P lending. As described in our analytical result, since some risky or low-income customers have turned to P2P platforms for funding, the decrease in credit investigation cost has caused a cost saving and the banks' managerial efficiency will increase.

Table 5 and 6 also show that the magnitudes of P2P lending effect are higher with small banks. LendingClub in the US serves as a dealer; lenders deposits their money in a pool of fund, and the P2P company dispatches the money to different borrowers. P2P platforms in this framework are more similar to traditional banking. Since large banks run nationwide business, so compared to local small banks, they are more prepared for this financial innovation and can cope with the sharp competition from P2P lending better.

Second, intangible assets (IA) are used to measure banks' fintech investments. Interestingly, Table 5 shows that the impacts of fintech investment are significantly positive for small banks, and Table 6 shows that the impacts of fintech investment are negative but not significantly for large banks. Since large banks are more prepared for providing fintech services, they invest more resources in computing equipment, data building, or data analysts training. The effects of these investments are not immediate, so these investments seem to have no or negative contribution to bank efficiency. Small banks, on the contrary, serve more local citizens and most of the fintech investments is on computer equipment, thus having an immediate contribution to loan services.

Finally, since the efficiency scores are restricted to be smaller than one, the values of R^2 are

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not too high for both Tobit and OLS regressions due to this restriction.

(ii) Deposit Efficiency (model 2)

First, Table 6 and 8 show that the coefficients of LnTD are most significantly positive for TE and PTE in large and small banks. This indicates that P2P lending has negative impacts on both large and small banks' scale efficiency (TE) and managerial efficiency (PTE) in deposits.

Since P2P lending platforms provide higher rate of return, and can invest with small amount of money. Both small individual and large cooperation customers will switch their money to these new investment targets. These deposit losses cannot be compensated by superior managerial skills and hence the impacts on both scale and managerial efficiency in deposits are negative. Interestingly, our Tobit model shows that the negative impact of P2P lending on managerial efficiency is almost double than the impacts on scale efficiency (i.e., 0.116 v.s. 0.058). P2P lending platforms provide borrowers' credit evaluation through online records. Since in local small banks, most customers deposits their money for saving, the managerial efficiency of small banks are affected by P2P lending more.

Second, Table 8 shows that the impacts of fintech investment are significantly positive for small banks, and Table 7 shows that the impacts of fintech investment are not significant for large banks. Again, this is because large banks are more prepared for providing fintech services, they invest more resources in computing equipment, data building, or data analysts training. The effects of these investments are not immediate, so these investments seem to have no or negative contribution to bank efficiency.

(ii) Loan vs Deposit Efficiency (model 1 vs model 2)

Table 5 and 7 show that the coefficient of LnTD is significantly negative in large banks' managerial loan efficiency, but significantly positive on large banks' managerial deposit efficiency. This indicates that P2P lending has "positive" impacts on large banks' managerial loan efficacy in loan but has "negative" impacts on large banks' managerial deposit efficiency. As explained, since some risky or low-income customers have turned to P2P platforms for funding, the decrease in credit investigation cost has caused a cost saving and the banks'

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managerial efficiency will increase. Large banks run nationwide business, so compared to local small banks, so they are more prepared for this financial innovation and can cope with the sharp competition from P2P lending better. However, because small individual and large cooperation customers will switch their money to P2P lending as alternative investment targets, these deposit losses cannot be compensated by superior managerial skills and hence the impacts on both scale and managerial efficiency in deposits are negative.

3.2.2 Performance

As described, LendingClub in the US and Zopa in the UK are operating with different frameworks. For LendingClub, the P2P platform serves as a dealer; for Zopa, the P2P platform can serves as a match maker. The intermediary role of P2P company in the US is similar to traditional banks. Therefore, in addition to the three aspects of influences on bank performance mentioned above, there can be a further negative impact from more competition in the first model. To justify this hypothesis, we study the effects of P2P lending on bank performance for both US and UK.

To compared the impacts of P2P lending in both countries on the same base, we also use bank performance as our dependent variable for large banks in the U.S. The data period is from 2000 to 2015, and run the OLS and panel data with fixed effect[6] model for pooled and panel data, respectively.

We use "net income" (NI) as our proxy for bank performance. When net income becomes higher, bank performance becomes higher. Moreover, Figure 1 shows that LnTD can be used as firm-specific proxy for P2P lending effect in the U.S. As for other control variables, similar to the variable choices in section 3.2.1. We use total assets, capital ratio, intangible assets, and number of employees. Our regression model is:

$$\mathrm{NI}_{it} = \beta_0 + \beta_1 LnTD_{it} + \beta_2 LnTA_{it} + \beta_3 CR_{it} + \beta_4 IA_{it} + \beta_5 LC_{it} + \varepsilon_{\mathrm{it}}. \quad (7)$$

Due to the data availability of banks in the UK, we cannot use DEA model to measure the efficiency scores. Instead, we collect financial data from the websites of 6 major UK banks (HSBS,

6 We have run the regressions with panel data random effects, but our results show that panel data fixed effects fit better.

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Barclays, Standard Chartered, Lloyds, Santander UK, and RBS) from 2005 to 2015, and run the OLS and panel data with fixed effect model for pooled and panel data, respectively.

Similarly with the U.S., we use "net income" (NI) as our proxy for bank performance. When net income becomes higher, bank performance becomes higher. Moreover, Figure 2 shows that LnTD can be used as firm-specific proxy for P2P lending effect in the UK. As for other control variables, similar to the variable choices for the U.S., we use total assets, capital ratio, intangible assets, labor cost, and a cross term with P2P lending and labor cost to indicate the overall or core business performance of bank. Labor cost is a proxy for the numbers of workers, and the cross term with P2P lending and labor cost measures whether the effect of P2P lending will change with the number of employers. Our regression model is:

$$\mathrm{NI}_{it} = \beta_0 + \beta_1 LnTD_{it} + \beta_2 LnTA_{it} + \beta_3 CR_{it} + \beta_4 IA_{it} + \beta_5 LC_{it} + \beta_6 LnTD * LC_{it} + \varepsilon_{\mathrm{it}}. \tag{8}$$

The regression results for equation (7) and (8) are presented in Table 9 and 10.

Table 9 shows that the coefficients of LnTD are positive and significantly in both OLS and panel data with fixed effect models. The result indicates that P2P lending has negative impacts on bank performance. At the same time, it is the same with the result of section 3.2.1; no matter what efficiency or performance we use, P2P lending has negative impacts on banks.

Table 10 shows that that the coefficients of LnTD are positive but not significantly in both OLS and panel data with fixed effect models. This indicates that P2P lending has negative but not significant impacts on bank performance. A possible explanation is that since Zopa operates as a match maker, so compared to LendingClub in the US, its competition impacts on the traditional banks are less severe and hence the effects are not significant.

Compared the results of US and UK, we can conclude that because the business model is similar with traditional banks, P2P lending in the U.S. has significantly negative impacts on banks. In UK, the role of P2P lending is a match maker, so its impacts is not significant like what they are in the U.S.

Next, the coefficients of IA are all significantly positive, showing that UK banks are well prepared for competition from P2P lending. The large fintech investments have already take effects and are making positive contributions to bank performance. Vives (2017) mentioned that there are positive and negative impact of fintech on banking. The positive impact is that fintech

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has the potential to lower the cost of intermediation and broaden the access to finance increasing financial inclusion. The negative impact is that new competitors are able to use hard information to erode the traditional relationship between bank and customer. Our results show that the positive impact has dominated in the UK.

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Table 9 Effect of P2P lending on bank performance in the U.S.

This table presents the regression results for the impact of LnTD on the dependent variable, NI (Net Income) for the banks in the US. The regression model is

$$NI_{it} = \beta_0 + \beta_1 LnTD_{it} + \beta_2 LnTA_{it} + \beta_3 CR_{it} + \beta_4 IA_{it} + \beta_5 LC_{it} + \varepsilon_{it}$$

We provide regression result for both OLS and Panel data with Fixed Effect model for pooled ad panel data, respectively. $LnTD_{it}$ is the proxy for P2P lending. We use five control variables (total assets, capital ratio, Intangible assets, labor cost, and interaction of labor cost) to indicate the overall or core business performance of banks. *, **, and *** measure the significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable **Net Income**	OLS (N=66)		Panal Data (N=66) (fixed effect)	
	Coefficient Estimate	P>|t|	Coefficient Estimate	P>|z|
Intercept	160,478	0.523	-406,258	0.167
LnTD	52,869 ***	0.000	54,636 ***	0.000
LnTA	- 49,989 ***	0.001	- 21,429	0.223
CR	- 331,466 **	0.024	-146,778	0.320
IA	0.004 ***	0.000	0.005 ***	0.000
LC	1.191 ***	0.000	0.670 *	0.051
Adj R^2	0.457		Hausman test	145.16 (prob> χ^2 =0.000)
R^2 / F	0.466/54.69		R^2 - within/between/overall	0.510/0.011/0.452

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Table 10 Effect of P2P lending on bank performance in UK

This table presents the regression results for the impact of LnTD on the dependent variable, NI (Net Income) for the 6 major banks in UK (HSBS, Barclays, Standard Chartered, Lloyds, Santander UK, and RBS) (Drake, 2001). The regression model is

$$NI_{it} = \beta_0 + \beta_1 LnTD_{it} + \beta_2 LnTA_{it} + \beta_3 CR_{it} + \beta_4 IA_{it} + \beta_5 LC_{it} + \beta_6 LnTD * LC_{it} + \varepsilon_{it}$$

We provide regression result for both OLS and Panel data with Fixed Effect model for pooled ad panel data, respectively. $LnTD_{it}$ is the proxy for P2P lending. We use five control variables (total assets, capital ratio, Intangible assets, labor cost, and interaction of labor cost) to indicate the overall or core business performance of banks. *, **, and *** measure the significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable **Net Income**	OLS (N=66)		Panal Data (N=66) (fixed effect)	
	Coefficient Estimate	P>∣t∣	Coefficient Estimate	P>∣z∣
Intercept	110,751 ***	0.000	66,420 *	0.093
LnTD	1,531	0.880	2,911	0.770
LnTA	- 22,045 **	0.030	- 14,598 **	0.168
CR	- 3,899	0.943	96,242	0.109
IA	0.214 *	0.062	0.375 ***	0.007
LC	3.713	0.335	0.733	0.889
LnTD*LC	- 0.375	0.537	- 0.174	0.838
Adj R^2	0.449		Hausman test	16,46 (prob> χ^2 =0.001)
R^2 / F	0.500/9.840		R^2 - within/between/overall	0.241/0.033/0.011

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4. Concluding Remarks

The development of P2P is the trend in financial sector. P2P makes many different impacts on banks. From positive aspect, P2P can lower the cost of credit investigation from banks, and from negative aspect, first P2P will attract people to invest their money to platforms rather than depositing in traditional banks because of higher interest rate. Second, people may transform their borrowing channel to P2P lending instead of traditional banks due to lower interest rate offered by P2P. It is hard to identify which impact is larger.

Thus, this current paper attempts to provide answers to this question by examining bank performance before and after P2P showing up. Because there are different business models of P2P around the world, they may cause the different results for banks' performance. We compare a P2P company called LendingClub in the U.S. which model is the lender puts money in a pool of funds, and a P2P company called Zopa in UK which model is that P2P offers a platform that borrowers and lenders can make a deal directly on the platform. In the front case, P2P lending company dispatches the money to different borrowers; thus in this pattern, lenders don't know the borrowers' information. In the latter case, lenders can observe borrowers' information. According to our empirical result, we conclude that the platform in the U.S. cases overall make negative impacts on bank performance significantly, because its functions more like a bank. On the contrary, there is no significantly impacts on banks' performance after P2P development in UK.

Finally, the reason why P2P can offer lower borrowing cost for borrowers, and higher investment return for investors is that most P2P platforms do not have many physical branches and labors, so their operating cost is lower. Moreover, the regulation cost of P2P is also lower than traditional banks. We know that traditional banking is a high restricted industry because of its systemic risk; however, the regulation is less strict on P2P in the past, leading to many risks of failure on P2P, and it is not good for banks and investors. It also causes plenty of problems on P2P failure. Hence, to reduce the problems, we suggest that governments should strengthen the rules with the development of P2P.

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Appendix

Here we briefly review the theoretical background for the efficiency scores, and reasons for the input and output variables used in calculating the efficiency scores.

Here we first briefly review the theoretical background for the efficiency scores, and reasons for the input and output variables used in calculating the efficiency scores.

First, DEA uses linear programming to estimate the relationship between goods and services (outputs) to assigned resources (inputs) (See Charnes et. al., 1978). The literature has proposed two assumptions on production technology: constant return to scale (CRS) and variable return to scale (VRS). Charnes, Cooper and Rhodes (1978) developed the CCR Model under the CRS assumption and calculate the technical efficiency scores (TE). TE represents the overall technical efficiency which measures the inefficiencies from the configuration of input/output and the size of operations. Banker, Charnes and Cooper (1984) developed the BCC Model under VRS assumption and calculate the pure technical efficiency scores (PTE). PTE measures the inefficiencies due to only managerial underperformance.[7]

Specifically,[8] let X be inputs and Y be n outputs. The input-oriented[9] CCR model solves the following linear programming problem for firm i:

$$\begin{aligned} &\min_{\theta} \theta \\ &s.t - y_i + Y\lambda \geq 0, \\ &\lambda \geq 0, \end{aligned} \tag{A1}$$

where θ is a scalar and λ is an n by 1 vector of constants. The value of θ is named as the TE efficiency score for firm I such that $0 \leq \theta \leq 1$, and TE represents the technical efficiency.

Banker et al. (1984) extend the CCR modle by considering VRS. Since not all firms are operating at the optimal scale, Banker et al. decompose the TE into pure technical efficiency (PTE)

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7 According to Kumar and Gulati (2008) and Coelli et al. (2005), the DEA method can be input or output orientated. The former determines the minimum input for which the observed production of the DMU is possible, while the latter determines the maimum output of the DMU given the observed inputs. Both CCR and BCC models are input-oriented.

8 See Hu et al. (2009).

9 The existing studies on banking efficiency have used the input-oriented approach. This is most likely due to the assumption that bank managers have higher control over inputs rather than outputs (Fethi and Pasiouras, 2009).

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and scale efficiency (SE). Hence, in the BCC modle, the convexity constraint, $N^{'}$, is added into (A1). The BCC model solves the following linear programming problem for firm i:

$$
\begin{gathered}
\min_{\theta} \theta, \\
s.t - y_i + Y\lambda \geq 0, \\
\theta x_i - X\lambda \geq 0, \\
N^{'}\lambda = 1 \\
\lambda \geq 0,
\end{gathered}
$$

where $N^{'}$ is an n by 1 vector. The value of θ is named as the PTE efficiency score. The TE core obtained from CCR can decompose into two components: SE and PTE. If there is a difference in the TE and PTE scores for firm, this indicates that the firms have scale inefficiency. The convexity constraint ensures that an inefficient firm is only benchmarked against firms with similar sizes. Second, in order to calculate the TE and PTE score, we follow Fethi and Pasiouras (2009) using numbers of labors, fixed assets and total interest expense as our input variables because these variables are factors that produce bank loans and deposits.

As described in the analytical model, P2P lending will affect commercial banks' loans and deposits. To distinguish the two aspects of effects, we use two groups of output variables in calculating the efficiency scores, i.e.,

Model 1: Input: employees, total fixed assets, and total interest expense
Output: **loans**, and total interest income
Model 2: Input: employees, total fixed assets, and total interest expense.
Output: **deposits**, and total interest income)

Model 1 and 2 are only different in the choice of output variables. Model 1 describes the efficiency on loans and Model 2 describes the efficiency on deposits. For each model, we calculate the technical efficiency scores (TE).and the pure technical efficiency scores (PTE) (see Charnes et al., 1978; Banker et al., 1984). Moreover, to examine whether the effects of P2P lending change with the banking scale, we follow Wolfe and Yoo (2018) in classifying banks with total assets greater than US$300 million as "large banks" and those with total assets under US$300

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million as "small banks". Table A6~A9 present the efficiency scores for large and small banks using model 1 and 2.

Table A1 Inputs and Outputs

The table presents the input and output variables used in our models. Following Fethi and Pasiouras (2009), we choose 3 input variables, and 2 different group output variables.

	Variable
Input	Numbers of workers
	Fixed assets
	Total interest expense
Output	Loans
	Deposits
	Total interest income

Table A2 Correlation Coefficient Matrix for large banks

The inputs and outputs variables should comply with the isotonicity premise; ie., the increase of an input will not cause a decrease in another. The following correlation coefficient matrix suggests that our results comply with the isotonicity premise.

	Loans	Deposits	Total nterest income
Numbers of workers	0.7252 (<0.0000)	0.6629 (<0.0000)	0.8255 (<0.0000)
Fixed asset	0.8421 (<0.0000)	0.8431 (<0.0000)	0.7915 (<0.0000)
Total interest expense	0.5980 (<0.0000)	0.5345 (<0.0000)	0.7996 (<0.0000)

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Table A3 Correlation Coefficient Matrix for small banks

The inputs and outputs variables should comply with the isotonicity premise; ie., the increase of an input will not cause a decrease in another. The following correlation coefficient matrix suggests that our results comply with the isotonicity premise.

	Loans	Deposits	Total interest income
Numbers of workers	0.5035 (<0.0000)	0.4934 (<0.0000)	0.5889 (<0.0000)
Fixed asset	0.2542 (<0.0000)	0.3173 (<0.0000)	0.1563 (<0.0051)
Total interest expense	0.3213 (<0.0000)	0.1839 (<0.0010)	0.6482 (<0.0000)

Table A4 Summary Statistics for input and output variables of large banks

The tables present the summary statistics for input and output variables. Data cover 20 large banks in the U.S. for the period 2000 to 2015.

Variables	Unit	Mean	St.Dev.	Min	Max
Numbers of workers	number	46,700	58,699	807	231,333
Fixed asset	Thousand	2,275,377	2,783,242	38,285	19,567,931
Total interest expense	Thousand	3,145,317	5,944,424	8,558	38,916,000
Loan	Thousand	10,977,843	14,970,911	27,190	69,719,000
Deposit	Thousand	210,075,330	308,565,579	2,684,118	1,439,404,000
Total interest income	Thousand	148,358,025	201,597,773	2,486,110	878,562,000

Table A5 Summary Statistics for input and output variables of small banks

The tables present the summary statistics for input and output variables. Data cover 20 small banks in the U.S. for the period 2000 to 2015.

Variables	Unit	Mean	St.Dev.	Min	Max
Numbers of workers	number	51	21	6	112
Fixed asset	Thousand	3,941	3,177	367	30,819
Total interest expense	Thousand	3,115	2,104	132	10,290
Loan	Thousand	121,526	48,442	9,137	270,973
Deposit	Thousand	162,028	54,229	11,950	284,489
Total interest income	Thousand	9,964	3,685	781	22,522

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Table A6 Efficiency Scores of Model 1 for Large Banks

Column 3 to 6 present the summary statistics of TE (technical efficiency) and PTE (pure technical efficiency) for 2000-2015. JRS and DRS indicate the numbers of banks under increasing or decreasing to scale. By Wolfe and Yoo (2018), large banks have total assets greater than US$300 million. The input variables in model 1 are employees, total fixed assets, and total interest expense. Output variables are loans, and total interest income.

Year	DEA	Obs	Mean	St. Dev.	Min	IRS	DRS
2000	TE	20	0.935	0.096	0.701	5	5
	PTE	20	0.973	0.069	0.738		
2001	TE	20	0.680	0.423	0.008	10	0
	PTE	20	0.795	0.367	0.210		
2002	TE	20	0.793	0.144	0.514	4	13
	PTE	20	0.887	0.142	0.547		
2003	TE	20	0.767	0.180	0.39	4	12
	PTE	20	0.879	0.177	0.394		
2004	TE	20	0.831	0.173	0.466	9	5
	PTE	20	0.918	0.153	0.512		
2005	TE	20	0.867	0.157	0.485	7	8
	PTE	20	0.937	0.110	0.629		
2006	TE	20	0.887	0.132	0.587	7	6
	PTE	20	0.943	0.110	0.605		
2007	TE	20	0.900	0.180	0.455	4	3
	PTE	20	0.947	0.135	0.545		
2008	TE	20	0.862	0.149	0.576	6	6
	PTE	20	0.927	0.102	0.695		
2009	TE	20	0.659	0.218	0.242	7	14
	PTE	20	0.753	0.216	0.415		
2010	TE	20	0.582	0.174	0.217	8	11
	PTE	20	0.662	0.199	0.244		
2011	TE	20	0.548	0.144	0.372	16	4
	PTE	20	0.637	0.151	0.405		
2012	TE	20	0.508	0.182	0.115	11	9
	PTE	20	0.580	0.222	0.125		
2013	TE	20	0.528	0.173	0.258	12	7
	PTE	20	0.605	0.172	0.470		
2014	TE	20	0.552	0.191	0.194	17	3
	PTE	20	0.611	0.189	0.319		
2015	TE	20	0.560	0.153	0.207	15	5
	PTE	20	0.630	0.140	0.419		

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Table A7 Efficiency Scores of Model 1 on Small Banks

Column 3 to 6 present the summary statistics of TE (technical efficiency) and PTE (pure technical efficiency) for 2000-2015. JRS and DRS indicate the numbers of banks under increasing or decreasing to scale. By Wolfe and Yoo (2018), small banks have total assets smaller than US$300 million. The input variables in model 1 are employees, total fixed assets, and total interest expense. Output variables are loans, and total interest income.

. Year	DEA	Obs	Mean	St. Dev.	Min	IRS	DRS
2000	TE	20	0.929	0.091	0.738	7	3
	PTE	20	0.970	0.080	0.787		
2001	TE	20	0.840	0.145	0.612	8	5
	PTE	20	0.916	0.129	0.621		
2002	TE	20	0.873	0.145	0.558	7	5
	PTE	20	0.935	0.128	0.559		
2003	TE	20	0.873	0.156	0.495	7	4
	PTE	20	0.900	0.158	0.502		
2004	TE	20	0.860	0.160	0.460	8	3
	PTE	20	0.904	0.154	0.566		
2005	TE	20	0.912	0.100	0.684	9	2
	PTE	20	0.940	0.088	0.743		
2006	TE	20	0.882	0.113	0.668	13	0
	PTE	20	0.975	0.104	0.677		
2007	TE	20	0.912	0.110	0.684	8	2
	PTE	20	0.954	0.085	0.718		
2008	TE	20	0.894	0.108	0.643	8	4
	PTE	20	0.952	0.085	0.672		
2009	TE	20	0.865	0.139	0.521	9	2
	PTE	20	0.894	0.130	0.552		
2010	TE	20	0.815	0.125	0.557	10	6
	PTE	20	0.832	0.123	0.558		
2011	TE	20	0.839	0.141	0.504	8	6
	PTE	20	0.892	0.139	0.507		
2012	TE	20	0.795	0.157	0.465	6	10
	PTE	20	0.840	0.160	0.468		
2013	TE	20	0.744	0.151	0.436	7	11
	PTE	20	0.883	0.134	0.622		
2014	TE	20	0.806	0.158	0.434	10	5
	PTE	20	0.851	0.145	0.439		
2015	TE	20	0.776	0.153	0.451	9	8
	PTE	20	0.836	0.140	0.483		

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Table A8 Efficiency Scores of Model 2 on Large Banks

Column 3 to 6 present the summary statistics of TE (technical efficiency) and PTE (pure technical efficiency) for 2000-2015. JRS and DRS indicate the numbers of banks under increasing or decreasing to scale. By Wolfe and Yoo (2018), large banks have total assets greater than US$300 million. The input variables in model 2 are employees, total fixed assets and total interest expense. Output variables are deposits, and total interest income

Year	DEA	Obs	Mean	St. Dev.	Min	IRS	DRS
2000	TE	20	0.837	0.081	0.734	2	16
	PTE	20	0.934	0.082	0.748		
2001	TE	20	0.939	0.064	0.820	1	6
	PTE	20	0.948	0.065	0.820		
2002	TE	20	0.889	0.097	0.738	4	11
	PTE	20	0.937	0.081	0.761		
2003	TE	20	0.850	0.114	0.689	4	11
	PTE	20	0.911	0.098	0.714		
2004	TE	20	0.931	0.082	0.784	7	2
	PTE	20	0.960	0.070	0.788		
2005	TE	20	0.908	0.098	0.726	9	3
	PTE	20	0.958	0.072	0.765		
2006	TE	20	0.966	0.055	0.825	7	0
	PTE	20	0.969	0.013	0.945		
2007	TE	20	0.970	0.045	0.838	2	9
	PTE	20	0.985	0.033	0.872		
2008	TE	20	0.841	0.283	0.066	7	2
	PTE	20	0.897	0.271	0.111		
2009	TE	20	0.653	0.245	0.228	14	4
	PTE	20	0.804	0.248	0.243		
2010	TE	20	0.343	0.314	0.023	17	1
	PTE	20	0.566	0.318	0.039		
2011	TE	20	0.331	0.232	0.068	18	1
	PTE	20	0.746	0.228	0.358		
2012	TE	20	0.591	0.269	0.131	14	2
	PTE	20	0.711	0.274	0.183		
2013	TE	20	0.299	0.224	0.058	18	0
	PTE	20	0.593	0.274	0.058		
2014	TE	20	0.503	0.233	0.182	16	1
	PTE	20	0.594	0.241	0.282		
2015	TE	20	0.43	0.266	0.141	15	3
	PTE	20	0.61	0.272	0.169		

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Table A9 Efficiency Scores of Model 2 on Small Banks

Column 3 to 6 present the summary statistics of TE (technical efficiency) and PTE (pure technical efficiency) for 2000-2015. JRS and DRS indicate the numbers of banks under increasing or decreasing to scale. By Wolfe and Yoo (2018), small banks have total assets smaller than US$300 million. The input variables in model 2 are employees, total fixed assets and total interest expense. Output variables are deposits, and total interest income

Year	DEA	Obs	Mean	St. Dev.	Min	IRS	DRS
2000	TE	20	0.928	0.093	0.724	7	3
	PTE	20	0.970	0.060	0.787		
2001	TE	20	0.840	0.145	0.612	8	5
	PTE	20	0.916	0.129	0.621		
2002	TE	20	0.873	0.145	0.558	7	5
	PTE	20	0.935	0.128	0.559		
2003	TE	20	0.873	0.156	0.495	6	4
	PTE	20	0.900	0.158	0.502		
2004	TE	20	0.860	0.160	0.460	8	3
	PTE	20	0.904	0.154	0.566		
2005	TE	20	0.907	0.108	0.652	9	2
	PTE	20	0.940	0.088	0.743		
2006	TE	20	0.882	0.113	0.668	13	0
	PTE	20	0.904	0.104	0.677		
2007	TE	20	0.912	0.11	0.684	8	2
	PTE	20	0.954	0.085	0.718		
2008	TE	20	0.894	0.108	0.643	8	4
	PTE	20	0.952	0.085	0.672		
2009	TE	20	0.785	0.189	0.436	10	3
	PTE	20	0.826	0.170	0.468		
2010	TE	20	0.823	0.160	0.427	10	6
	PTE	20	0.797	0.171	0.433		
2011	TE	20	0.769	0.202	0.346	9	6
	PTE	20	0.837	0.181	0.406		
2012	TE	20	0.745	0.196	0.304	6	11
	PTE	20	0.809	0.184	0.429		
2013	TE	20	0.733	0.196	0.363	7	10
	PTE	20	0.847	0.162	0.426		
2014	TE	20	0.776	0.192	0.434	10	6
	PTE	20	0.824	0.164	0.439		
2015	TE	20	0.821	0.16	0.491	8	7
	PTE	20	0.812	0.178	0.428		

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