Journal of Applied Economics and Business Research
JAEBR, 9(4): 186-196 (2019)

Does P2P Lending Affect Bank Lending? Evidence from China

Tsung-Pao Wu[1]
Beijing Institute of Technology, China

Hung-Che Wu
Nanfang College of Sun Yat-Sen University, China

Bodan Chen
Beijing Institute of Technology, China

Qihong Lin
Beijing Institute of Technology, China

Tiandi Zou
Beijing Institute of Technology, China

Abstract

Previous studies have shown that some kinds of causal linkages exist between peer-to-peer lending (P2PL) and bank lending (BL). In this study, we stress that previous studies have focused on one or a few regions. In addition, we employ a multivariate panel Granger causality approach, which is adapted from a Granger causality test (Granger, 2003). The longitudinal/panel data used in this study allow us to offer a comparable sample and result to simultaneously identify the relationship between P2PL and BL among China's eight major regions. This work uses a multivariate panel Granger causality test to examine the causal relationship between P2PL and BL in China's eight major areas for the period from 2014M01 to 2018M08, accounting for both dependency and heterogeneity across areas. The results of this study support evidence for the P2PL leading hypothesis in the areas such as Shanghai, Shandong and Guangdong, while the BL leading hypothesis relationship supports evidence for the areas like Jiangsu. However, there is an interactive causal relationship between P2PL and BL in the areas such as Zhejiang and Hubei. In addition, the result of a neutrality hypothesis supports two of these eight major areas (Beijing and Sichuan). The empirical findings of this work provide important policy implications for China's eight major areas.

Keywords: P2PL; BL; Bootstrap multivariate panel Granger causality; China

JEL Codes: C33, E44, E52

[1] Correspondence Author: Tsung-Pao Wu; wutsungpao@yahoo.com.hk

1. Introduction

How is the relationship between nexus peer-to-peer lending (P2PL) and bank lending (BL) market? There has already been interest in the relationship between P2PL and BL although the theoretical ground of such relationship is not explicitly defined. Due to the increasing popularity of networks, P2PL has been developing very rapidly, particularly in China. However, some Chinese banks, including the Bank of China, Agricultural Bank of China, Industrial and Commercial Bank of China and the China Construction Bank, have launched their own P2PL platforms. By the end of 2018, these banks had formally established more than 20 P2PL platforms. P2PL is recognized to have a positive effect on long-run BL through different channels. Over the past several decades the P2PL destinations worldwide have experienced inflows of different capital as the result of increase in demand for loan services, both for use and investment purposes. It has long been recognized that P2PL has an impact on BL (e.g. Belleflamme et al., 2015; Chen et al., 2012; Colombo et al., 2015; Cumming and Johan, 2016; Cumming and Zhang, 2016; Dorfleitner et al., 2016; Hota et al., 2015; Iyer et al., 2009, 2016; Lin et al., 2013; Liu et al., 2015).

P2PL is perceived as increasing overall financial activities, and the increase in these activities is generally considered desirable; namely, the positive impact of P2PL on financial activities is frequently described. Also, P2PL is recognized to have a positive effect on short-term, mid-term or long-term financial and economic growth through different channels. First, P2PL is a new form of loan origination in the credit market. This type of loan market is designed to complement traditional BL to meet the small loan needs of individuals and small and medium enterprises. Second, the P2PL platform can quickly assess and assign risk grades through the use of information technology instead of relying on delegated monitoring with banks as intermediaries. Finally, lenders have the opportunity to handle the financial and personal information provided by the borrowers and directly offer a loan that meets their investment criteria. As a result, lenders can get the money they need on P2PL for a short period of time which is relative to BL. However, it would be interesting and useful to determine whether there is a complementary relationship between BL and P2PL platforms or there is a competitive relationship between them.

This study investigates the causal relationship between P2PL and BL in China's eight major areas using the regional causality test developed by Kónya (2006) to determine the dynamic and causal relationship between P2PL and BL. This procedure will undoubtedly allow the specific effects of areas to be more readily uncovered. We examine whether there is a causal relationship between growth in P2PL and BL using a bootstrap multivariate panel Granger causality test through a sample of China's eight major areas over the period from 2014M01 to 2018M08. This is the first study to employ a bootstrap multivariate panel Granger causality test to examine the relationship between P2PL and BL in China's eight major areas. This study is expected to fill the gap in the current literature on growth in the P2PL and BL.

2. Literature Review

The relationship between P2PL and BL includes much research that attempts to identify the relationship. However, previous research has confirmed that P2PL can certainly affect BL. Most previous studies have conducted the relationship between P2PL and BL (e.g. Culkin et al., 2016; Dorfleitner et al., 2016; Duarte et al., 2012; Fraser et al., 2015; Guo et al., 2016; Iyer et al., 2009, 2016; Kankanhalli et al., 2016; Klievink et al., 2017; Lin et al., 2013; Loureiro and Gonzalez, 2015; Mild et al., 2015; Pope and Sydnor, 2011; Ravina, 2008; Thuan et al., 2016; Yuan and Hesieh, 2016).

Based on the past literature, P2PL focuses on the behavior of traders and the risk of trading in this market. In the study of the behavior of traders, the researchers mainly discuss herding behaviors. Because of the risk of information asymmetry, traders exhibit herding behaviors in P2PL (Lee and Lee, 2012). As for the risk of trading, the researchers focus on the factors that affect credit risk in the P2PL market and P2PL risk regulations. Lenders can evaluate one-third of credit risk using both soft and hard information about borrowers (Iyer et al., 2009). For example, Emekter et al. (2015) point out that the credit classification of borrowers plays an important role in loan defaults and that charging higher interest rates to high-risk borrowers cannot compensate for the risk of loss. Chaffee and Rapp (2012) describe that P2PL is risky and that it is therefore necessary to build an evolving regulatory regime for an evolving industry. Herzenstein et al. (2008) find that strategic herding behavior contributes to P2PL bidders individually and collectively. Using a multinomial logit market share model, Lee and Lee (2012) find strong evidence of herding and its diminishing marginal effect as bidding advances.

However, other sources, such as the risk of trading and the credit classification of borrowers and P2PL risk regulation, have undoubtedly attracted a lot of attention to the most recent financial activity. Verstein (2011) proposes a preferable regulatory scheme designed to preserve and discipline P2P lending's innovative mix of social finance, micro-lending and disintermediation. Guo et al. (2016) design an instance-based credit risk assessment model that can effectively improve investment performance compared to existing methods in P2PL. In terms of the risk of trading, the researchers focus on the factors that affect credit risk in the P2PL market and P2PL risk regulations. Lenders can evaluate one-third of credit risk using both soft and hard information about borrowers (Iyer et al., 2009). For example, some studies note that the borrower's soft information, including social ties, can benefit both borrowers and lenders (Freedom and Jin, 2014; Lin et al., 2013) and that the borrower's hard information, including demographic characteristics and financial strength, have an influence on the likelihood of funding success (Herzenstein et al., 2008).

Brill (2010) presents that P2PL may directly competes with traditional bank lines of credit. The online P2PL market primarily provides micro credits to small businesses and individuals that often have difficulties in obtaining loans from banks. Zhang et al. (2017) apply the bootstrap panel causality approach, indicating that the causality between bank loans and peer-to-peer loans varies across areas with different conditions in China. Although the bootstrap panel causality approach can be applied to an independent variable, there are more than two arguments in the real relationship between the variables, indicating that the statistical results are misleading. Accordingly, this work used the equation system for multivariate panel Granger causality analysis to optimize and supplement the previous research. In addition, it used two control variables for other important variables that, if omitted, would cause the estimated coefficients to be biased. Therefore, we adopted the P2PL and BL interest rates as control variables one and two respectively. It would be interesting and useful to determine whether there is a causal link between bank and P2P loans in the long run.

3. Data Collection and Methodology

The data for China's eight major areas were collected from Wang Dai Zhi Jia[2]. The dataset employed in this study included the period from 2014M01 to 2018M08 for China's eight major areas (i.e. Beijing, Shanghai, Jiangsu, Zhejiang, Shandong, Hubei, Guangdong and Sichuan). The

[2] Here is the website for the data: http:// www.wdzi.com

sample period was decided purely by data availability on the measure for the P2PL activities. All variables were used in their natural log form. The used data included the BL to measure the performance of the BL activities and P2PL to measure the performance of the P2PL activities for each area. Besides, this work used control variables for other important variables that, if omitted, would cause the estimated coefficients to be biased. Therefore, we adopted the P2PL and BL interest rates as control variables one and two respectively. Figure 1 plots the P2PL index versus the BL index across eight major areas.

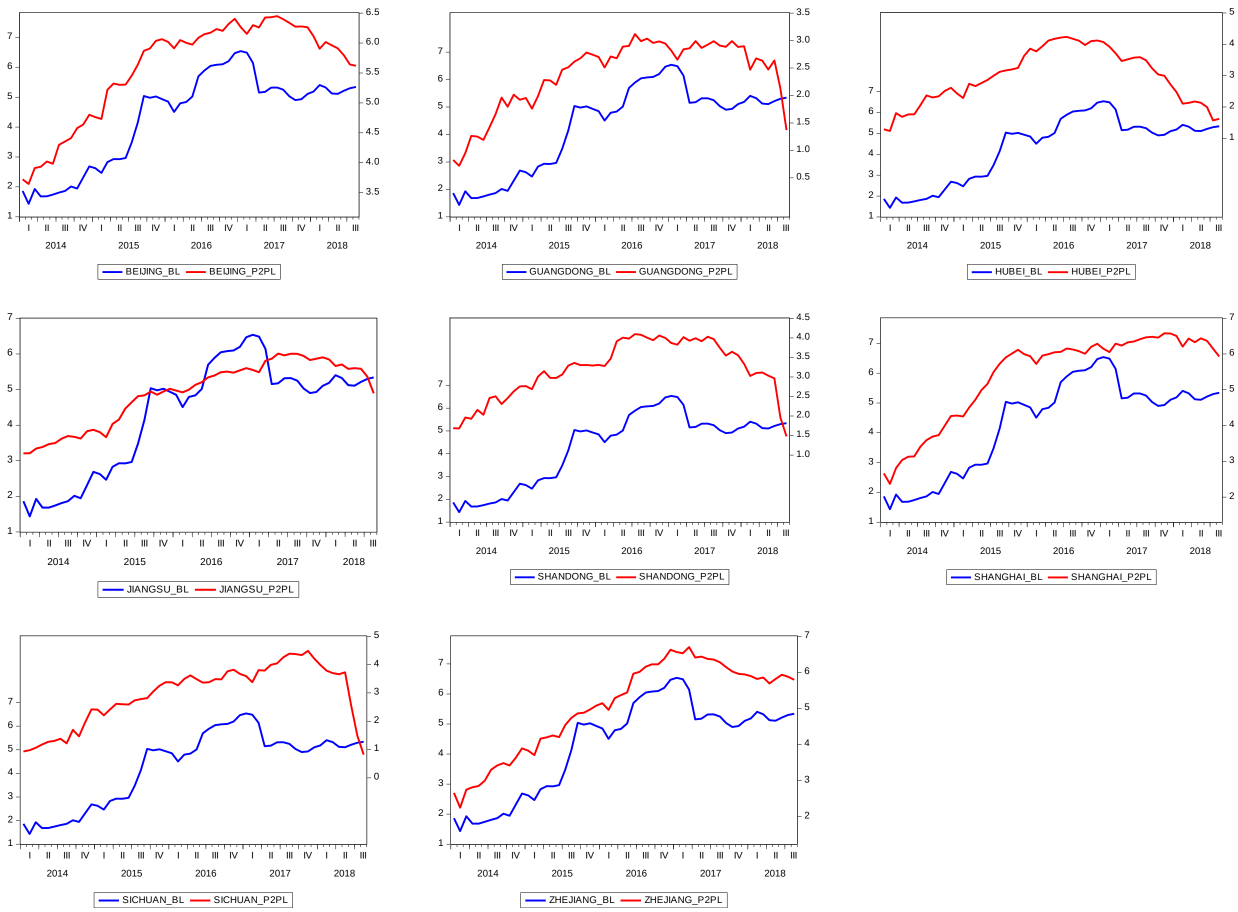

Figure 1: The BL Versus the P2PL Across China's Eight Major Areas.

3.1. Testing cross-sectional dependence and slope homogeneity

One of the important assumptions in the bootstrap multivariate panel causality is the existence of cross-sectional dependency among the areas in the panel. In the case of cross-sectionally correlated errors, the estimator from the regression system described with the seemingly unrelated regression (SUR) is more efficient than the estimator with the pooled ordinary least squares model. However, the ordinary least square (OLS) approach does not consider cross-sectional dependency. The first issue in panel causality analysis focuses on accounting for possible cross-sectional dependence across areas. Cross-sectional dependency is the most important issue when dealing with panel Granger causality across China's eight major areas. Since there are vast areas with various levels of economic growth and an increasing amount of integration among areas in China, a shock occurs within one area and influences other areas, such as endowments and geographical differences, which are felt around the areas. Accordingly, it is necessary to carry out a series of cross-sectional dependence tests when we examine the panel data causality between P2PL, and BL among China's eight major areas considered in this work. The other issue in panel data analysis is to decide whether the slope coefficients are homogeneous. Causality running from one variable to another due to the imposition of a joint restriction for the whole panel is the strong null hypothesis (Granger, 2003). Moreover, the homogeneity assumption for the parameters fails to capture heterogeneity due to specifically regional characteristics (Breitung, 2005). The panel data analysis concentrates on deciding whether the slope coefficients are homogeneous. Interested readers can refer to the cross-sectional dependence and slope homogeneous tests proposed by Bahmani-Oskooee and Wu (2018) in detail.

3.2. Multivariate panel Granger causality analysis

The presence of both cross-sectional dependency and heterogeneity across China's eight major areas requires a multivariate panel Granger causality approach that accounts for such dynamics. The panel Granger causality test proposed by Kónya (2006) fails to account for both cross-sectional dependence and area-specific heterogeneity. This approach is based on the SUR estimation of the set of equations and Wald tests with individual and area-specific bootstrap critical values.

The equation system for a multivariate panel Granger causality analysis includes two sets of equations that can be extended in this study. This paper follows Bahmani-Oskooee and Wu, 2018; Wu et al., 2018; Wu and Wu, 2016, 2018a, 2018b, 2019a, 2019b) and the equation system for multivariate panel Granger causality analysis including two sets of equations that can be written as:

$$\begin{pmatrix} y_{1,t} \\ \vdots \\ y_{N,t} \end{pmatrix} = \begin{pmatrix} \alpha_{1,1} \\ \vdots \\ \alpha_{1,N} \end{pmatrix} + \begin{pmatrix} \beta_{1,1,1} & \cdots & \beta_{1,1,ly_1} \\ \vdots & \ddots & \vdots \\ \beta_{1,N,1} & \cdots & \beta_{1,N,ly_1} \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ \vdots \\ y_{N,t-ly_1} \end{pmatrix} + \begin{pmatrix} \delta_{1,1,1} & \cdots & \delta_{1,1,x_1} \\ \vdots & \ddots & \vdots \\ \delta_{1,N,1} & \cdots & \delta_{1,N,x_1} \end{pmatrix} \begin{pmatrix} x_{1,t-1} \\ \vdots \\ x_{N,t-lx_1} \end{pmatrix}$$
$$+ \begin{pmatrix} \gamma_{1,1,1} & \cdots & \gamma_{1,1,lw_1} \\ \vdots & \ddots & \vdots \\ \gamma_{1,N,1} & \cdots & \gamma_{1,N,lw_1} \end{pmatrix} \begin{pmatrix} w_{1,t-1} \\ \vdots \\ w_{N,t-lw_1} \end{pmatrix} + \begin{pmatrix} \lambda_{1,1,1} & \cdots & \lambda_{1,1,lz_1} \\ \vdots & \ddots & \vdots \\ \lambda_{1,N,1} & \cdots & \lambda_{1,N,lz_1} \end{pmatrix} \begin{pmatrix} z_{1,t-1} \\ \vdots \\ z_{N,t-lz_1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,1,t} \\ \vdots \\ \varepsilon_{1,N,t} \end{pmatrix} \quad (1)$$

where β_1, δ_1, γ_1 and λ_1 are $N\ x\ ly_1$, $N\ x\ lx_1$, $N\ x\ lw_1$ and $N\ x\ lz_1$ matrices, and y ,x, w and z are $ly_1\ x 1$, $lx_1\ x 1$, $lw_1\ x 1$ $lz_1\ x 1$ and matrices, respectively.

$$\begin{pmatrix} x_{1,t} \\ \vdots \\ x_{N,t} \end{pmatrix} = \begin{pmatrix} \alpha_{2,1} \\ \vdots \\ \alpha_{2,N} \end{pmatrix} + \begin{pmatrix} \beta_{2,1,1} & \cdots & \beta_{2,1,ly_2} \\ \vdots & \ddots & \vdots \\ \beta_{2,N,1} & \cdots & \beta_{2,N,ly_2} \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ \vdots \\ y_{N,t-ly_2} \end{pmatrix} + \begin{pmatrix} \delta_{2,1,1} & \cdots & \delta_{2,1,lx_2} \\ \vdots & \ddots & \vdots \\ \delta_{2,N,1} & \cdots & \delta_{2,N,lx_2} \end{pmatrix} \begin{pmatrix} x_{1,t-1} \\ \vdots \\ x_{N,t-lx_2} \end{pmatrix}$$
$$+ \begin{pmatrix} \gamma_{2,1,1} & \cdots & \gamma_{2,1,lw_1} \\ \vdots & \ddots & \vdots \\ \gamma_{2,N,1} & \cdots & \gamma_{2,N,lw_1} \end{pmatrix} \begin{pmatrix} w_{1,t-1} \\ \vdots \\ w_{N,t-lw_1} \end{pmatrix} + \begin{pmatrix} \lambda_{2,1,1} & \cdots & \lambda_{2,1,lz_2} \\ \vdots & \ddots & \vdots \\ \lambda_{2,N,1} & \cdots & \lambda_{2,N,lz_2} \end{pmatrix} \begin{pmatrix} z_{1,t-1} \\ \vdots \\ z_{N,t-lz_2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{2,1,t} \\ \vdots \\ \varepsilon_{2,N,t} \end{pmatrix} \quad (2)$$

 ISSN 1927-033X

where β_2, δ_2, γ_2 and λ_1 are $N\ x\ ly_2$, $N\ x\ lx_2$, $N\ x\ lw_1$ and $N\ x\ lz_2$ matrices, and y, x, w and z are $ly_2\ x1$, $lx_2\ x1$, $lw_1\ x1$ $lz_2\ x1$ matrices, respectively.

In the equation systems (1) and (2), y refers to an indicator of P2PL, x is referred to as BL, w refers to the P2PL interest rate as a control variable 1, and z is referred to as the BL interest rate, which is considered as a control variable 2. N is the number of panel members, t is the time period (t = 1,…, T), and l is the lag length. The bootstrap critical values are obtained from 10,000 replications. The selection of the optimal lag structure is determined by minimizing the Schwarz Bayesian Criterion from one to four lags (Kónya, 2006). It should be noted that we have tried different lag lengths including five and six lags, but it appears that the Schwarz Information Criterion (SIC, also referred to as the Bayesian Information Criterion) becomes bigger. Consequently, this work selected lags from one to four and found that the model with two lags was best suited for our data giving its smallest SIC value.

4. Empirical Results

As previously outlined, testing cross-sectional dependency and slope homogeneity in a study of multivariate panel Granger causality is crucial for selecting the appropriate estimator. In addition, accounting for cross-sectional dependency and area-specific heterogeneity in the empirical analysis is also crucial as the areas are highly integrated and their economic relations are characterized by a high degree of localization. This study therefore begins to determine whether cross-sectional dependency and heterogeneity exist across the concerned areas. The existence of cross-sectional dependence is shown in Table 1. In this study, we conducted four different tests (i.e. LM, CD_{lm}, CD and LM_{adj}). It is clear that the null of no cross-sectional dependency across the areas is strongly rejected at conventional significance levels, implying that the SUR method is more appropriate than the area-by-area OLS estimation (Zellner, 1962). This finding implies that a shock occurring in one of these areas seems to have been transmitted to the other areas. Table 1 also reports the results from two slope homogeneity tests ($\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$). Both tests reject the null hypothesis of slope homogeneity, supporting area-specific heterogeneity. The rejection of slope homogeneity implies that a multivariate panel Granger causality analysis imposes a homogeneity restriction on the variable of interest which leads to misleading inferences. In this respect, the multivariate panel Granger causality analysis based on the estimation of a panel vector auto-regression and/or panel vector error correction model using a generalized method of moments or pooled ordinary least square estimator is an inappropriate approach to detect causal linkages between P2PL and BL in China’s eight major areas.

The presence of cross-sectional dependency and heterogeneity across these areas provides evidence on the suitability of the multivariate panel Granger causality approach. The results of the multivariate bootstrap panel Granger causality analysis are reported in Tables 2 and 3. Table 2 shows that one-way Granger causality runs from P2PL to BL in Shanghai, Shandong and Guangdong. The study results provide evidence for the P2PL leading hypothesis for these areas, and Table 3 shows that one-way Granger causality running from the BL to P2PL can be found in Jiangsu. The results therefore support evidence for the BL leading hypothesis.

 ISSN 1927-033X

Table 1: Cross-sectional Dependence and Homogeneous Tests of China's Eight Major Areas.

Methods Cross-sectional dependence test	Test Statistics
CD_{BP}	118.511***
CD_{lm}	11.548***
CD	12.166***
LM_{adj}	18.259***
Homogeneous test	
$\tilde{\Delta}$	74.681***
$\tilde{\Delta}_{adj}$	5.466***
Swamy Shat	255.889***

Notes: *** indicate significance at the 0.01 level, respectively.

CD_{BP} , CD_{lm} , CD and LM_{adj} are cross-sectional dependence tests of Breusch and Pagan (1980), Pesaran (2004), and Pesaran et al. (2008), respectively. $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$ are slope homogeneity tests of Pesaran and Yamagata (2008). Swamy (1970) develops the slope homogeneity test that allows cross-sectional heteroscedasticity.

Table 2: P2PL Does Not Granger Cause BL

Area	Coefficient	Wald Statistics	Bootstrap Critical Value		
			1%	5%	10%
Beijing	0.002	0.455	13.257	7.004	5.286
Shanghai	0.001	0.372*	0.810	0.521	0.363
Jiangsu	-0.001	0.136	1.560	1.003	0.683
Zhejiang	-0.005	0.557*	1.930	0.786	0.427
Shandong	0.083	0.937**	0.988	0.647	0.581
Hubei	0.101	0.798**	1.293	0.738	0.375
Guangdong	0.307	1.156***	1.033	0.579	0.400
Sichuan	0.000	0.002	1.721	0.841	0.395

Notes: 1. ***, ** and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.
2. Bootstrap critical values are obtained from 10,000 replications.

Table 3: BL Does Not Granger Cause P2PL

Area	Coefficient	Wald Statistics	Bootstrap Critical Value		
			1%	5%	10%
Beijing	0.048	1.785	11.409	7.483	5.514
Shanghai	0.012	0.067	12.795	5.991	5.058
Jiangsu	0.045	4.627*	9.923	6.608	4.200
Zhejiang	0.242	14.923***	11.397	9.336	8.074
Shandong	0.005	0.967	7.985	6.841	5.174
Hubei	-0.014	11.929***	10.892	8.516	5.844
Guangdong	0.000	0.006	12.838	7.587	5.675
Sichuan	0.005	0.812	17.719	8.746	5.964

Notes: 1. * and *** indicate significance at the 0.1 and 0.01 levels, respectively.
2. Bootstrap critical values are obtained from 10,000 replications.

The different results for P2PL and BL of the sample are displayed in Table 4. A comparison for China's eight major areas of multivariate panel Granger causality between P2PL and BL is

 ISSN 1927-033X

made. First, the empirical results of this study indicate that in the areas such as Shanghai, Shandong and Guangdong, P2PL stimulates BL, and the BL growth thus depends on P2PL, implying that negative P2PL shocks and P2PL reduction policies may depress BL. The governments of these areas need to emphasize the P2PL to increase financial activities. The results provide evidence for the P2PL leading hypothesis for these areas. Second, a relationship between BL to P2PL is found in the areas like Jiangsu, indicating that BL increases the demand for P2PL and then leads to the development of P2PL in this area. The results provide evidence for the BL leading hypothesis for this area.

Table 4: A Summary of Granger Causality between P2PL and BL for China's Eight Major Areas

	H_0: P2PL Does Not Granger Cause BL					H_0: BL Does Not Granger Cause P2PL				
			Bootstrap Critical Value					*Bootstrap Critical Value*		
Area	*Coefficient*	*Wald Statistics*	*1%*	*5%*	*10%*	*Coefficient*	*Wald Statistics*	*1%*	*5%*	*10%*
Beijing	0.002	0.455	13.257	7.004	5.286	0.048	1.785	11.409	7.483	5.514
Shanghai	0.001	0.372*	0.810	0.521	0.363	0.012	0.067	12.795	5.991	5.058
Jiangsu	-0.001	0.136	1.560	1.003	0.683	0.045	4.627*	9.923	6.608	4.200
Zhejiang	-0.005	0.557*	1.930	0.786	0.427	0.242	14.923***	11.397	9.336	8.074
Shandong	0.083	0.937**	0.988	0.647	0.581	0.005	0.967	7.985	6.841	5.174
Hubei	0.101	0.798**	1.293	0.738	0.375	-0.014	11.929***	10.892	8.516	5.844
Guangdong	0.307	1.156***	1.033	0.579	0.400	0.000	0.006	12.838	7.587	5.675
Sichuan	0.000	0.002	1.721	0.841	0.395	0.005	0.812	17.719	8.746	5.964

Notes: 1. ***, ** and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.
2. Bootstrap critical values are obtained from 10,000 replications.

Third, an interaction causal relationship between P2PL and BL is found in the areas such as Zhejiang and Hubei. The P2PL and BL are endogenous, indicating that these two factors mutually influence each other, and that this reinforcement may have important implications for the conduct of BL or P2PL development policies in the areas. The feedback hypothesis argues that the causal relationship between P2PL and BL expansion appears bi-directional, implying that a push in both areas is beneficial. Recognizing the causal relationship between P2PL and BL is of great importance. Lean et al. (2014) propose that the P2PL and BL in special circumstances have a significant relationship between them, indicating that both of them are capturing the benefits from the P2PL and BL expansion. In this study, the enthusiasm in promoting P2PL or aggressive BL expansions may have a strong effect on the real scenario. When a reciprocal causal relationship is found, an appropriate resource allocation of planning for the P2PL and BL and other industries is important and necessary.

Finally, the study findings for the remaining two areas (i.e. Beijing and Sichuan) seem to support the neutrality hypothesis, indicating that neither P2PL nor BL is sensitive to the other. The neutrality between P2PL and BL suggests that P2PL does not exert an adverse impact on BL, and that P2PL is not affected by BL. The neutrality between P2PL and BL is attributed to a relatively small contribution of P2PL to overall output. Accordingly, P2PL may have little or no impact on BL activities in these areas. There are eight areas investigated in this work. Two of the eight areas show that there is no direct relationship between P2PL and BL. The result may be shocked or bemused for this proportion result. Many previous studies have revealed the positive relationship between P2PL and BL. However, it is dangerous for an area to make a policy using the positive relationship to formulate industrial strategies. The empirical result of this study shows the comparisons for China's eight major areas (see Table 5).

Table 5: Results of Comparisons for China's Eight Major Areas.

Area	P2PL vs. BL	BL vs. P2PL	Effect
Beijing	None	None	None
Shanghai	P2PL→BL	None	P2PL leading
Jiangsu	None	BL→P2PL	BL leading
Zhejiang	P2PL→BL	BL→P2PL	Feedback
Shandong	P2PL→BL	None	P2PL leading
Hubei	P2PL→BL	BL→P2PL	Feedback
Guangdong	P2PL→BL	None	P2PL leading
Sichuan	None	None	None

Notes: 1.→ denotes Granger causality from the left-hand side variable to the right-hand side variable.
2.← denotes Granger causality from the right-hand side variable to the left-hand side variable.

In sum, the empirical results indicate that the direction of causality between P2PL and BL may be determined by various factors. We speculate that the size of an area' economy, the area level of openness and the level of travel restrictions are plausible factors generating the differences among China's eight major areas. In addition to these factors, the degree of dependence on P2PL and the level of housing economic development may be considered as additional determinants. The time-series approaches overlook cross-sectional dependency across areas in the causality test. Accordingly, they may result in misleading inferences in terms of the nature of causality between P2PL and BL. We find strong evidence for the existence of cross-sectional dependence among these areas. It may be concluded that policy implications driven from the causality approach account for cross-sectional dependency and seem more appropriate. Furthermore, we also detect cross-regional heterogeneity in the panels of China's eight major areas, implying that each area develops its P2PL policies.

5. Conclusions and Research Limitations

This work applied the multivariate panel Granger causality approach to examine whether P2PL and BL used the data from China's eight major areas over the period from 2014M1 to 2018M8. The empirical results of this study provide evidence for the P2PL leading hypothesis in the areas such as Shanghai, Shandong and Guangdong, while the BL leading hypothesis relationship supports evidence for the area like Jiangsu. In addition, the interaction causal relationship between P2PL and BL is found in the areas such as Zhejiang and Hubei. The empirical findings of this study provide important policy implications for these areas. A main limitation of this study is recommended that related variables such as bank loan balances, P2P lending balances, short-term benchmark lending rates or M2 as a control variable are not considered and this inclusion is recommended. Consequently, future studies should focus on domestic GDP or among others as a control variable while analyzing the effects of P2PL and BL activities. As for future research, employing different economic methods such as time-frequency domain, bootstrap rolling-window or novel wavelet (3D surfaces) re-examines the causal relationship between the P2PL and BL activities in these areas.

 ISSN 1927-033X

Acknowledgement
This study was supported by Department of Education of Guangdong Province (Grant Number 2018WTSCX214).

References

Bahmani-Oskooee M, Wu TP. 2018. On the Relation between Housing and Stock Markets in 118 OECD Countries: A Bootstrap Panel Causality Test. *Journal of Real Estate Portfolio Management* 24:2, 121-133.

Belleflamme P, Omrani N, Peitz M. 2015. The Economics of Crowdfunding Platforms. Information Economics and Policy 33, 11-28.

Breitung J. 2005. A Parametric Approach to the Estimation of Cointegration Vectors in Panel Data. *Econometric Reviews* 24:2, 151-173.

Brill A. 2010. Peer-to-Peer Lending: Innovative Access to Credit and the Consequences of Dodd-Frank. Legal Backgrounder 25: 35. Available at https://s3.us-east-2.amazonaws.com/washlegal-uploads/upload/legalstudies/legalbackgrounder/12-3-10Brill_LegalBackgrounder.pdf.

Breusch T and Pagan A. 1980. The LM Test and Its Application to Model Specification in Econometrics. *Review of Economic Studies* 47:1, 239-254.

Chaffee EC, Rapp GC. 2012. Regulating Online Peer-to-Peer Lending in the Aftermath of Dodd-Frank: In Search of an Evolving Regulatory Regime for an Evolving Industry. *Washington & Lee Law Review* 69, 485-533.

Chen H, Chiang RH, Storey VC. 2012. Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly* 36:4, 1165-1188.

Colombo MG, Franzoni C, Rossi-Lamastra C. 2015. Internal Social Capital and the Attraction of Early Contributions in Crowdfunding. *Entrepreneurship Theory and Practice* 39:1, 75-100.

Culkin N, Murzacheva E, Davis A. 2016. Critical Innovations in the UK Peer-to-Peer (P2P) and Equity Alternative Finance Markets for Small Firm Growth. *The International Journal of Entrepreneurship and Innovation* 17:3, 194-202.

Cumming D, Johan S. 2016. Crowdfunding and entrepreneurial internationalization, in: Dai N., Siegel, D. (Eds.), *Entrepreneurial Finance: Managerial and Policy Implications*. The World Scientific Publishers, Singapore. Available at https://ssrn.com/abstract=2711894

Cumming D, Zhang Y. 2016. Alternative Investments in Emerging Markets: A Review and New Trends. *Emerging Markets Review* 29, 1-23.

Dorfleitner G, Priberny C, Schuster S, Stoiber J, Weber M, de Castro I, Kammler J. 2016. Description-Text Related Soft Information in Peer-to-Peer Lending–Evidence from Two Leading European Platforms. *Journal of Banking & Finance* 64, 169-187.

Duarte J, Siegel S, Young L. 2012. Trust and Credit: The Role of Appearance in Peer-to-Peer Lending. *The Review of Financial Studies* 25:8, 2455-2484.

Emekter R, Tu Y, Jirasakuldech B, Lu M. 2015. Evaluating Credit Risk and Loan Performance in Online Peer-to-Peer (P2P) Lending. *Applied Economics* 47:1, 54-70.

Fraser, S, Bhaumik SK, Wright M. 2015. What do We Know About Entrepreneurial Finance and Its Relationship with Growth?. *International Small Business Journal* 33:1, 70-88.

Freedom, SM, Jin GZ. 2014. The Signaling Value of Online Social Networks: Lessons from Peer-to-Peer Lending. *Working paper* No. 19820, NBER, Cambridge, MA.

Granger CW. 2003. Some Aspects of Causal Relationships. *Journal of Econometrics* 112:1, 69-69.

Guo Y, Zhou W, Luo C, Liu C, Xiong H. 2016. Instance-Based Credit Risk Assessment for Investment Decisions in P2P Lending. *European Journal of Operational Research* 249:2, 417-426.

Herzenstein M, Andrews RL, Dholaki UM, Lyandres E. 2008. The Democratization of Personal Consumer Loans? Determinants of Success in Online Peer-to-Peer Lending Communities. Available at https://pdfs.semanticscholar.org/127f/3b1106835ccee15d2cdf1e1099cf699247cd.pdf.

Hota C, Upadhyaya S, Al-Karaki JN. 2015. Advances in Secure Knowledge Management in the Big Data Era. *Information Systems Frontiers* 17:5, 983-986.

Iyer R, Khwaja AI, Luttmer EFP, Shue K. 2009. Screening in New Credit Markets: Can Individual Lenders Infer Borrower Creditworthiness in Peer-to-Peer Lending?. AFA 2011 *Denver Meetings Paper*. Available at https://ssrn.com/abstract=1570115 or http://dx.doi.org/10.2139/ssrn.1570115.

Iyer R, Khwaja AI, Luttmer EFP, Shue K. 2016. Screening Peers Softly: Inferring the Quality of Small Borrowers. *Management Science* 62:6, 1554-1577.

Kankanhalli A, Hahn J, Tan S, Gao G. 2016. Big Data and Analytics in Healthcare: Introduction to the Special Section. *Information Systems Frontiers* 18:2, 233-235.

Klievink B, Romijn BJ, Cunningham S, de Bruijn H. 2017. Big Data in the Public Sector: Uncertainties and Readiness. *Information Systems Frontiers* 19:2, 267-283.

Kónya L. 2006. Exports and Growth: Granger Causality Analysis on OECD Countries with a Panel Data Approach. *Economic Modelling* 23:6, 978-992.

Lean HH, Chong SH, Hooy CW. 2014. Tourism and Economic Growth: Comparing Malaysia and Singapore. *International Journal of Economics and Management* 8:1, 139-157.

Lee E, Lee B. 2012. Herding Behavior in Online P2P Lending: An Empirical Investigation. *Electronic Commerce Research and Applications* 11:5, 495-503.

Lin M, Prabhala NR, Viswanathan S. 2013. Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending. *Management Science* 59:1, 17-35.

Liu D, Brass D, Lu Y, Chen D. 2015. Friendships in Online Peer-to-Peer Lending: Pipes, Prisms, and Relational Herding. *MIS Quarterly* 39:3, 729-742.

Loureiro YK, Gonzalez L. 2015. Competition Against Common Sense: Insights on Peer-to-Peer Lending as a Tool to Allay Financial Exclusion. *International Journal of Bank Marketing* 33:5, 605-623.

Mild A, Waitz M, Wöckl J. 2015. How Low Can You Go? Overcoming the Inability of Lenders to Set Proper Interest Rates on Unsecured Peer-to-Peer Lending Markets. *Journal of Business Research* 68:6, 1291-1305.

Pope DG, Sydnor JR. 2011. What's in a Picture? Evidence of Discrimination from Prosper. com. *Journal of Human Resources* 46:1, 53-92.

Pesaran MH. 2004. General Diagnostic Tests for Cross Section Dependence in Panels. Cambridge *Working Papers in Economics* No. 0435, Faculty of Economics, University of Cambridge, England.

Pesaran MH, Ullah A, Yamagata T. 2008. A Bias-Adjusted LM Test of Error Cross-section Independence. *The Econometrics Journal* 11:1, 105-127.

Pesaran MH, Yamagata T. 2008. Testing Slope Homogeneity in Large Panels. *Journal of Econometrics* 142:1, 50-93.

Ravina E. 2008. Love & Loans: The Effect of Beauty and Personal Characteristics in Credit Markets. Available at https://ssrn.com/abstract=1107307.

Swamy PAVB. 1970. Efficient Inference in a Random Coefficient Regression Model. *Econometrica: Journal of the Econometric Society* 38:2, 311-323.

Thuan NH, Antunes P, Johnstone D. 2016. Factors Influencing the Decision to Crowdsource: A Systematic Literature Review. *Information Systems Frontiers* 18:1, 47-68.

Verstein A. 2011. The Misregulation of Person-to-Person Lending. *UCDL Rev*. 45, 445-530.

Wu TP, Wu HC. 2016. The Relationship between International Tourism Receipts and Economic Growth in the China Economy. Paper presented at the 6th Advances in Hospitality and Tourism Marketing and Management Conference, Guangzhou, China

Wu TP, Wu, HC. 2018a. The Causal Nexus between International Tourism and Economic Development. *Tourism Analysis* 23:1, 17-29.

Wu TP, Wu HC. 2018b. The Influence of International Tourism Receipts on Economic Development - Evidence from China's 31 Major Regions. *Journal of Travel Research* 57:7, 871-882.

Wu TP, Wu HC. 2019a. The Link between Tourism Activities and Economic Growth: Evidence from China's Provinces. *Tourism and Hospitality Research* 19:1, 3-14.

Wu TP, Wu HC. 2019b. Tourism and Economic Growth in Asia: A Bootstrap Multivariate Panel Granger Causality. *International Journal of Tourism Research* 21:1, 87-96.

Wu TP, Wu HC, Liu SB, & Hsueh SJ. 2018. The Relationship between International Tourism Activities and Economic Growth: Evidence from China's Economy. *Tourism Planning & Development* 15:4, 365-381.

Yuan STD, Hsieh CF. 2018. An Impactful Crowdsourcing Intermediary Design-A Case of a Service Imagery Crowdsourcing System. *Information Systems Frontiers* 20:4, 841-862.

Zellner A. 1962. An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias. *Journal of the American Statistical Association* 57:298, 348-368.

Zhang Z, Hung K, Chang T. 2017. P2P Loans and Bank Loans, the Chicken and the Egg, What Causes What? Further Evidence from a Bootstrap Panel Granger Causality Test. *Applied Economics Letters* 24:19, 1358-1362.

 ISSN 1927-033X