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Small Business Owners' Fintech Credit in Crises: Theory and Evidence from Farmers under the COVID-19.

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Abstract

This paper examines the COVID-19 impact on Chinese farmers' peer-to-peer (P2P) borrowings using transaction-level data. Our difference-in-differences estimation results suggest that farmers from the most pandemic-affected region, Hubei province, substantially reduced their P2P loans by 13% compared to other areas. Besides, we find a significantly lower equilibrium interest rate change, indicating a more dominant force on the demand side. Finally, we evaluate the lockdown policy, showing that provinces with larger logistics capacities exhibit more considerable credit declines. Overall, our study suggests that Fintech lending functions as an alternative financing channel during the pandemic, though the demand shrinkage dominates the supply.

Keywords: Small Business; COVID-19 Crisis; Fintech Credit.

JEL codes: D14; Q12; Q14.

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1 Introduction

The Coronavirus Disease 2019 (COVID-19) hit the Chinese economy tremendously, especially entrepreneurs and small business owners (Dai *et al.*, 2021). It is well-documented that their financing problems are severely affected and upsurging after the pandemic's outbreak (Liu *et al.*, 2021). Similar to small business owners, farmers are also gravely impacted by the COVID-19.[1] Farmers, often categorized as households, actually are small business owners with production capacities. However, the pandemic's impact on Chinese farmers' microfinance has not been addressed in the small business owners' Fintech financing literature (Narayan, 2021), and this paper intends to bridge the gap.

Understanding this relationship between farmer's microfinance and the COVID-19 is important for the following reasons. On the one hand, compared to other small businesses, farmers have limited access to banks' credit (Rui and Xi, 2010). They rely more heavily on informal credit markets to finance their working capital in normal times, let alone during the COVID-19 pandemic. Thus, whether the Fintech market provides alternative financing in the COVID-19 crisis is vital to farmers. On the other hand, the COVID-induced shrinking demand for agricultural products suppresses farming production, which in turn affects farmers' credit demand.[2] Hence, the investigation on farmers intriguingly provides us an ideal setting to study the supply-demand mechanism of Fintech borrowings in the COVID-19 crisis.

Using novel transaction-level data from a farmer-specific Fintech peer-to-peer (P2P) lending platform in China, Eloancn, this paper empirically analyzes the impact of the COVID-19 on Chinese farmers' P2P borrowings.[3] Concretely, we define Hubei province as

[1] Organisation for Economic Co-operation and Development (OECD) and the Food and Agriculture Organization (FAO) report a destructive impact of the COVID-19 on food demand (OECD, 2020).

[2] Previous studies document that farmers' credits were adversely affected during crisis periods (Peoples *et al.*, 1992; Paulson and Sherrick, 2009), primarily because of the sudden demand contraction in agricultural products (Briggeman *et al.*, 2009; Ellinger and Tirupattur, 2009).

[3] To our best knowledge, only China has a farmer-specific P2P lending platform, and the rural population accounts for more than 40% of the total Chinese population.

the treatment group since it is the most COVID-affected region in China, and compare Hubei farmers' P2P loans with those from other areas before and after the pandemic outbreak. Based on the propensity score-matched sample, our difference-in-differences (DD) estimation shows a 13% reduction in Hubei farmers' equilibrium Fintech credit. This decrease could be driven by either less demand from the farmers or less supply from the P2P platform. To distinguish the mechanism, we test the equilibrium interest rate change and find a significantly lower rate after the crisis, indicating a more dominant force on the demand side. Besides, we provide suggestive evidence to rule out the possibility that the observed decline in farmers' P2P loans results from easing traditional financing. Hence, the Fintech platform functions as an alternative financing channel in the COVID-19 crisis, though the demand shrinkage dominates the supply.

These findings motivate us to construct a partial equilibrium model from the demand side, via which we could further examine why farmers shrink borrowings in a crisis. The theoretical model assumes that farmers need to borrow to finance their working capital at an exogenous interest rate before producing agricultural goods. When the aggregate demand slumps due to the crisis (e.g., the COVID-19 outbreak), any individual farmer would contract the production. Consequently, they reduce their working capital and also the equilibrium borrowings. This propagation mechanism is not pertaining to the COVID-19 pandemic and is general for demand-driven crises.

Besides, to look into the effect of the COVID-specific lockdown policy, we incorporate transportation cost into the theoretical model. We show that transportation disruption due to the inter-province lockdown policy would increase farmers' production costs and inhibit farmers' microloans. Our empirical test echoes this prediction. Using the province's logistics capacity as the continuous treatment, we find provinces with larger logistics capacities exhibited a more salient decline in farmers' P2P loans. The result was more pronounced in the pandemic-affected region. This study on the lockdown policy brings additional novel implications on Fintech lending during crisis periods since transportation was little affected in previous crises.

All the above results about farmers' Fintech credit in the COVID-19 crisis hold at the aggregate level. Our examination of the extensive margin, i.e., the change in the aggregate number of P2P loans, presents similar statistical significance but larger point estimates than the deal-level ones. Such difference between the intensive and extensive margin also supports our demand-driven mechanism.

The remainder of the paper is as follows. Section 2 reviews the related literature. Section 3 sets up the theoretical model and derives testable propositions. Section 4 introduces the data source and identification strategy. Section 5 presents our main empirical results. Conclusion remarks are made in Section 6.

2 Literature Review

Our paper builds on a growing number of COVID-19 literature. The first thread investigates the financial markets, such as stock market responses (Bannigidadmath *et al.*, 2021; Bing, 2021; Li, 2021; Narayan, 2021; Narayan *et al.*, 2020; Narayan *et al.*, 2021; Phan and Narayan, 2020; Sharma, 2020), exchange rate market reactions (Iyke, 2020) and systematic risks (Lan *et al.*, 2020). The second thread of literature studies the pandemic's impact on firms, such as cash holding (Qin *et al.*, 2020), bank loan (Zhang *et al.*, 2021), outward direct investment (Zhao *et al.*, 2020), innovation (Han and Qian, 2020), and sustainable growth (Chen *et al.*, 2021). Most related COVID-19 works examine the pandemic's impact on small business owners (Bartik *et al.*, 2020; Fairlie, 2020; Liu *et al.*, 2021) and domestic credit to private owners (Appiah-Otoo, 2020). To our best knowledge, there is no prior research concentrating on their Fintech financing behaviors in the pandemic context.

This study also complements the growing literature on households' financial responses in crises. Papers in this literature (e.g., Gallagher and Hartley, 2017; Deryugina *et al.*, 2018) mainly aim at natural disasters from the household financing perspective, while we concentrate on the interaction between global crises and small businesses' Fintech borrowings. Though a growing literature studies household response to the COVID-19 (Li *et al.*, 2020; Yue *et al.*, 2020; Yue *et al.*, 2021), this paper exclusively focuses on farmers' credit responses. Especially, we categorize farmers as small business owners instead of households because they obtain financing for production purposes rather than consumption motives. Farmers' production is vulnerable to crisis, which may affect the credit demand. Hence, studying Fintech borrowings from the perspective of small business owners enables us to examine the supply-demand mechanism in a crisis and contribute to the literature with new implications.

Our work is also closely related to the literature studying the alternative financing role of Fintech lending. A seminal paper by Tang (2019) unveils the substitution and complementary effects between banks and the P2P market in the US after banking deregulation in normal times. Differently, our work focuses on crisis periods during which the supply of P2P credit might also slump. Our findings contribute to the literature in three dimensions. First, we establish the crisis-specific empirical evidence and document an equilibrium reduction in farmers' Fintech credit. Second, we are among the first to distinguish the supply-demand mechanism and recognize Fintech financing's role in a crisis. Third, we construct a demand-side theoretical model to disentangle the propagation mechanism of borrowing shrinkage in response to a crisis.

3 Theoretical Framework

In this section, we present a partial equilibrium model to study the responses of farmers' borrowings to the COVID-19 crisis. According to previous empirical studies, the aggregate demand of the agriculture commodities shrank during crisis periods, thus affecting farmers' income and financial health (Briggeman *et al.*, 2009; Ellinger and Tirupattur, 2009).[4] Similarly, a theoretical work by Basu and Bundick (2017) states that aggregate demand is dominant and determines output and its components in the short run. Hence, we are motivated to construct our partial equilibrium model from the demand side, and discuss the supply-demand mechanism in our empirical analysis.

The model admits a continuum of monopolistically competitive intermediate farming producers indexed by $i \in [0, 1]$. Each farmer produces differentiated agricultural goods y_i using rented capital services k_i and labor inputs l_i with the following Cobb-Douglas technology:

$$y_i = (k_i)^\alpha (l_i)^{1-\alpha}, \tag{3.1}$$

where α is the capital-input share.

Following Jermann and Quadrini (2012), we assume that a farmer needs to borrow an intra-period loan b_i to finance its working capital (seeds, fertilizers, farm implements, etc). The working capital is required to cover the production costs at the beginning of each period, given by the following constraint

$$b_i = r_k k_i + w l_i, \tag{3.2}$$

where r_k and w are the capital rental rate and the wage rate, respectively.

After realizing its periodic revenue, the farmer repays the intra-period loan at the end of period at an exogenous interest rate r, which indicates that the farmer's total cost is $(r_k k_i + w l_i)(1 + r_i)$ in each period. Thus, under the perfectly competitive factor market assumption, the farmer's problem is to choose the optimal factors for production, k_i and l_i, that minimizes its total cost:

$$\min_{k_i, l_i} (r_k k_i + w l_i)(1 + r), \tag{3.3}$$

[4] Released by the National Bureau of Statistics (NBS), as farmers' major customers, the catering sector underwent a 44.3% drop in its revenue in the first quarter of 2020 compared to the same period last year. The contraction in demand decreased the GDP in the agriculture-related industry by 3.2% in the same period.

subject to its production function (3.1).

The cost minimization principle implies the following first-order conditions with respect to k_i and l_i:

$$(1+r)r_k = \alpha \frac{y_i}{k_i^*} mc, \tag{3.4}$$

$$(1+r)w = (1-\alpha) \frac{y_i}{l_i^*} mc, \tag{3.5}$$

where variables with * denote the optimal (equilibrium) states, and the marginal cost mc satisfies:

$$mc = (1+r) \left(\frac{r_k}{\alpha}\right)^{\alpha} \left(\frac{w}{1-\alpha}\right)^{1-\alpha}. \tag{3.6}$$

All farmers have the same marginal cost mc because factor prices (r_k and w) are the same across farmers due to the free movement of production factors (capital and labor).

The summation of (3.4) and (3.5) implies

$$(1+r)\left(r_k k_i^* + w l_i^*\right) = y_i mc. \tag{3.7}$$

After plugging the equation (3.2) into (3.7), we have the farmer's optimal loan amount:

$$b_i^* = \frac{y_i}{1+r} mc. \tag{3.8}$$

Apparently, the optimal working capital loans b_i^* is determined by the production of y_i, given exogenous factor prices (r_k and w), interest rate r and marginal cost mc in a partial equilibrium framework.

To determine the production of a specific intermediate good y_i, we study the demand from a final good producer (such as a catering business). Without loss of generality, we assume the competitive final good producer bundles a continuum of intermediate goods y_i

using the following production technology

$$y = \left(\int_0^1 y_i^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{3.9}$$

where $\epsilon > 1$ is the elasticity of substitution.

The final good producer choose optimal demand for y_i and maximizes its profit $y - \int_0^1 p_i y_i di$, taking all intermediate goods' prices p_i as given.[5] The maximization problem implies

$$y_i^* = (p_i)^{-\epsilon} y. \tag{3.10}$$

The equilibrium intermediate agricultural production y_i^* is proportionate to the exogenous demand from the whole economy y, but inversely proportional to its price p_i.

With the determined optimal factor inputs (k_i^* and l_i^*) and the optimal production y_i^*, the monopolistically competitive farmer set the price p_i to maximize its real profits subject to an exogenous transportation cost κ_j in each province.

$$\max_{p_i} p_i y_i^* - mc y_i^* - \kappa_j y_i^*, \tag{3.11}$$

where κ_j measures the per unit transportation cost to farmers from province j. The first-order condition for p_i implies

$$p_i^* = \frac{\epsilon}{\epsilon - 1}(mc + \kappa_j) \tag{3.12}$$

Plugging equation (3.12) into (3.10) and (3.8), we have

$$b_i^* = \frac{\left[\frac{\epsilon}{\epsilon-1}(mc + \kappa_j)\right]^{-\epsilon} y}{1+r} mc. \tag{3.13}$$

[5] We take the final good as the numeraire and normalize its price to 1.

The partial derivative of equilibrium borrowings b_i^* with respect to the exogenous demand y indicates:

$$\frac{\partial b_i^*}{\partial y} = \frac{\left[\frac{\epsilon}{\epsilon-1}(mc+\kappa_j)\right]^{-\epsilon}}{1+r} mc > 0, \tag{3.14}$$

Intuitively, when the aggregate demand slumps due to the crisis (e.g., the COVID-19 outbreak), any individual farmer would refrain from his/her production. Consequently, they reduce their working capital and also the equilibrium borrowings. Be noted that this propagation mechanism is not pertaining to the COVID-19 pandemic and is general for demand-driven crises. We state the following proposition in the COVID-19 context for a mapping of our empirical test.

Proposition 1 *The COVID-19 depresses farmers' borrowings, and such negative effect would be more pronounced in more seriously affected regions.*

Similarly, the partial derivative of b_i^* with respect to the transportation cost κ_j implies

$$\frac{\partial b_i^*}{\partial \kappa_j} = -\epsilon \frac{\left(\frac{\epsilon}{\epsilon-1}\right)^{-\epsilon}(mc+\kappa_j)^{-\epsilon-1} y}{1+r} mc < 0, \tag{3.15}$$

Intuitively, a higher transportation cost κ_j induce farmers to charge a higher price p_i^*, which consequently reduce agricultural outputs and farmers' borrowings. The following proposition captures the implication of the COVID-specific province-wide lockdown policy.

Proposition 2 *The disruption of transportation caused by the COVID-19 would inhibit farmers' microfinancing needs.*

4 Data and Identification Strategy

4.1 Data Source

Our data of farmers' P2P borrowings are from Eloancn. Founded in 2007, Eloancn is now ranked in the top 18 online P2P lending platforms in China. It is the only P2P platform targeted exclusively at farmers, according to WDZJ (2018). As Chinese farmers had long been suffering from traditional financing (Beck *et al.*, 2015), Eloancn rapidly gained its market share via providing credits to farmers and obtained strategic investment from Legend Holdings in 2014.[6] Currently, Eloancn covers 21 provinces with over 1,200 districts and counties. It has availed nearly 480,000 farmers' access to internet finance, echoing China's national initiative of helping the "Three Rurals" (i.e., rural industry, rural area, and rural residents).[7]

The COVID-19 outbreak did not affect the normal functioning of Eloancn. By the end of June 2020, the platform completed 952,330 loans with a cumulative credit amount of 65.04 billion RMB. Thus, the Eloancn data could be considered as a major source of Chinese farmers' alternative financing channels. This transaction-level dataset also includes borrowers' detailed demographic information, such as salary and experience levels.[8] The key variables in this paper are defined and summarized in Appendix Table I.

[6]Although some Chinese P2P platforms encountered a financial explosion (in Chinese: *Baolei*) from 2015 to 2018, Eloancn, as a regulated P2P institution, still experienced an upward trend in attracting loan investment in the following years (WDZJ, 2018).

[7]Eloancn admits an online application mode so that farmers could easily register and upload their necessary credentials through the Eloancn APP (Dongfang Net, 2016). After this simplified verification procedure, farmers could immediately initiate the P2P loan via the Eloancn platform.

[8]One deficiency of this dataset is the lack of unsuccessful P2P loans' information.

4.2 Identification Strategy

To assess the COVID-19 pandemic's impact on farmers' P2P borrowings, we employ a difference-in-differences (DD) strategy based on the matched sample. Concretely, we treat the *Wuhan Lockdown* policy announcement as the pandemic outbreak, and compare farmers' P2P loans before (i.e., January 23, 2019, to April 7, 2019) and after (i.e., January 23, 2020, to April 7, 2020) the announcement.[9] It is worth noting that we choose the same period in these two consecutive years for deseasonalization, as farming is usually featured by seasonality.

We define the P2P borrowers from Hubei province as the treatment group since Hubei has the most death and confirmed cases according to the National Health Commission (See Appendix Table II). In contrast, we take P2P borrowers from other provinces as the control group. The specific DD model at the *deal level* is as follows:

$$Y_{it} = \beta_0 + \beta_1(\text{Post}_t \times \text{Hubei}_i) + \mathbf{X}_i + \mu_i + \eta_t + \epsilon_{it}, \tag{4.1}$$

where Y_{it} is the natural logarithm of a P2P loan amount. Post_t is a dummy variable that equals one if the loan is made after the *Wuhan lockdown* (i.e., January 23, 2020) and zero otherwise. Hubei_i is a dummy variable that equals one if borrower i is from Hubei province and zero otherwise. Borrower i's demographic information (*Female, House Ownership, Previous P2P Loans, Salary*) are also controlled, captured by vector $\mathbf{X}_i$.

Moreover, we include the province (μ_i) and month×year (η_t) fixed effects to control unobserved time-invariant province factors and the nationwide macroeconomic shocks in each month×year, respectively. Note that the terms Post_t and Hubei_i are absorbed by the province and time fixed effects, and thus we omit them from Eq. (4.1). The standard error

[9]Wuhan (the capital city of Hubei province) is the city first reporting pneumonia cases and setting cordon sanitaire in the prevention of further spread. The *Wuhan Lockdown* on transit came in effect on January 23, 2020, and was lifted on April 8, 2020, signaling the first wave of the COVID-19 outbreak in China was temporarily abated, followed by the resumption of schools and business activities.

is clustered at the province level to account for any potential serial correlations within each region. Our primary coefficient of interest, β_1, is the impact of the COVID-19 outbreak on Hubei farmers' P2P loans relative to those from other provinces.

4.3 Propensity Score Matching and Summary Statistics

Our raw deal-level sample contains 17,609 loans, and 1.21% of the loan deals are from Hubei farmers.[10] One potential concern is that Hubei farmers could be systematically different from non-Hubei ones in many aspects, which might bias our estimation. Hence, we use the propensity score matching (PSM) method and match Hubei and non-Hubei farmers across time (month×year) and some observable individual characteristics.[11]

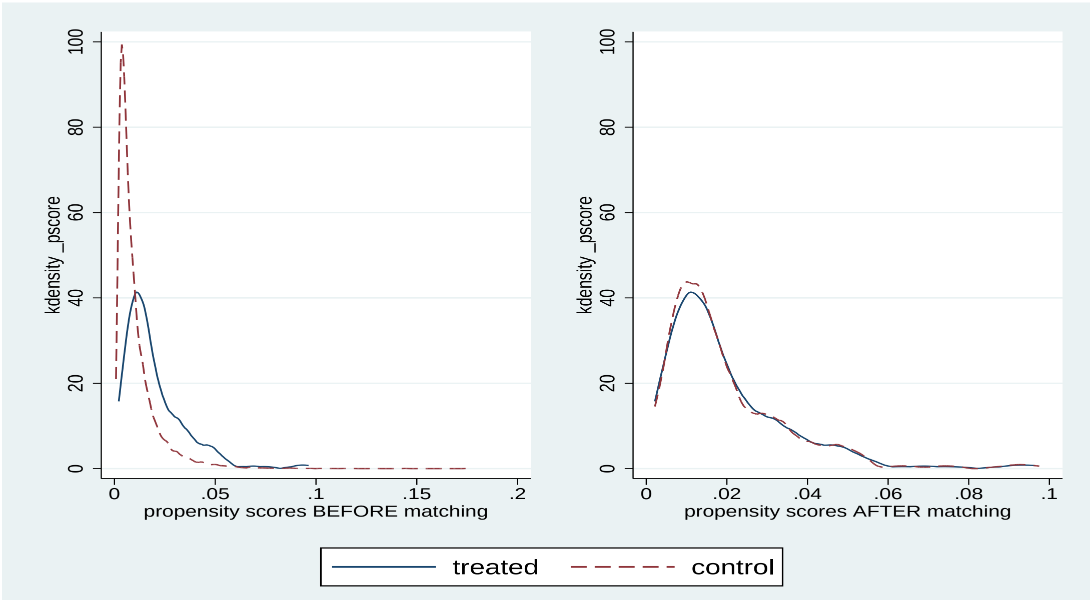
Figure 1 shows the kernel density graphs before and after the PSM. Apparently, the control group line becomes closer to the treatment group line in our matched sample, meaning that Hubei and non-Hubei farmers' attributes are similar after the matching. Therefore, our subsequent analysis would be based on this matched sample.

We present the summary statistics in Table 1. The matched sample has 1,074 loans, with an average value of approximately 67,000 RMB and an average interest rate of about 15%. Among the matched sample, 17.4% of the loan deals are from Hubei, a natural consequence of the 1-to-5 matching strategy. Most of the farming borrowers are male and homeowners. Their average annual income is less than 120,000 RMB (i.e., salary level less than 1), and 62% of them have previous P2P experience.

[10] We argue this seemingly low proportion of Hubei loans is reasonable and consistent with other widely used Chinese household surveys. For instance, Hubei farmers account for 1.16% of total farmers, according to the latest release of China Family Panel Studies (CFPS) in 2018.

[11] The personal characteristics include gender, house ownership, salary, previous P2P loans, age, education, marital status, and working experience. Due to the relatively small sample size of the treatment group, we use a 1-to-5 matching algorithm based on a logit model.

Figure 1: Kernel Density Graphs



Notes: This figure shows the kernel density plots before and after the PSM. More specifically, we match Hubei and non-Hubei farmers across time (month-year) based on some observable individual characteristics (i.e., gender, house ownership, salary, previous P2P loans, age, education, marital status, and working experience). We use a 1-to-5 matching algorithm based on a logit model.

Table 1: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Amount	1,074	67,365.61	32,559.18	300	190,200
Interest Rate	1,074	15.068	0.549	9.2	21
Hubei	1,074	0.174	0.379	0	1
Female	1,074	0.186	0.389	0	1
House Ownership	1,074	0.709	0.455	0	1
Salary	1,074	0.967	0.798	0	2
Previous P2P Loans	1,074	0.623	0.485	0	1

Notes: This table presents the descriptive statistics of all variables of our matched sample using the PSM method. Amount is the P2P deal value that a farmer borrows. Interest Rate defines the P2P loan interest rate. Hubei is a dummy variable indicating that whether a borrower is from Hubei province or not. Female is a dummy variable that equals one if the borrower is a female and zero otherwise. House Ownership is an indicator variable that equals one if the borrower has an apartment and zero otherwise. Salary represents a borrower's annual income level, ranging from 0 (if below 120,000 RMB) to 2 (if above 240,00 RMB). Previous P2P Loans is a dummy variable that equals one if a borrower has past records in P2P loans and zero otherwise. All continuous variables are winsorized at the 5th and 95th percentiles to mitigate the concern of extreme values.

5 Empirical Results

5.1 Parallel Trend Test

Before proceeding to the DD results, we check the validity through the parallel trend test. Concretely, the treatment group (i.e., deals from Hubei province) interacts with the month×year dummy in the same period before the shock (i.e., January to March 2019).[12] As shown in Appendix Table III, all lagged interaction coefficients are not statistically significant in the pre-period. Thus, the parallel trend assumption of the DD strategy is satisfied.

5.2 Main Results

We present the DD estimation results in Table 2. Column (1) suggests a statistically significant adverse effect on the equilibrium P2P loans from Hubei's farmers. Quantitatively, Hubei farmers contracted their P2P loans by 13% after the pandemic's outbreak, compared to those from non-Hubei regions. Column (3) reports the result when we use a continuous measure for the pandemic severity (*Death*), which is defined as the total provincial death cases scaled by the national sum as of April 7, 2020. These empirical findings are in line with *Proposition 1* derived from our equilibrium model.

Supply-Demand Mechanism Theoretically speaking, the decrease in equilibrium loan amount could be driven by either less demand from farmers or less supply from P2P investors. To distinguish the dominance, we replace the original dependent variable with the equilibrium interest rate and re-estimate Eq (3.1). Column (2) of Table 2 shows that the equilibrium interest rate decreased significantly by 6.7% after the COVID-19 crisis, indicating a more dominant force on the demand side since farmers always desire a low loan rate to cut costs

[12] We use the last period prior to pandemic (i.e., April 2019) as the baseline.

Table 2: The Impact of the COVID-19 on Farmers' P2P Loans

Variables	(1) Ln(Amount)	(2) Interest Rate	(3) Ln(Amount)	(4) Interest Rate
Post × Hubei	-0.130** (0.061)	-0.067* (0.038)		
Post × Death			-0.133** (0.063)	-0.069* (0.039)
Constant	10.935*** (0.004)	15.072*** (0.002)	10.935*** (0.004)	15.072*** (0.002)
Month × Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Individual Characteristics	Yes	Yes	Yes	Yes
Observations	1,074	1,074	1,074	1,074
R-squared	0.098	0.045	0.098	0.045

Notes: The dependent variables of Columns (1) and (3) are the natural logarithm of a P2P loan amount of borrower i in month year t, and the dependent variables of Columns (2) and (4) are the interest rate of the P2P loan. Post_t is a dummy variable that equals one if the loan is made after the *Wuhan lockdown* (i.e., January 23, 2020) and zero otherwise. Hubei_i is a dummy variable that equals one if borrower i is from Hubei province and zero otherwise. Death is a continuous measure for the pandemic severity, defined as the total provincial death cases scaled by the national sum as of April 7, 2020. Standard errors, clustered at the province level, are shown in brackets. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

while lenders intend to raise the interest rate to reap benefits. The result still holds in Column (4) of the *Death* variable. This demand dominating evidence backs up the narrative of our theoretical framework, and echoes the previous crisis literature that the shrinking demand for agriculture commodities during crisis periods put farmers' income and financial health at risk (Briggeman *et al.*, 2009; Ellinger and Tirupattur, 2009). In our context, pandemic-affected farmers would face a more plummeting demand and therefore curb their working capital's microfinancing.

Alternative Financing Mechanism Understanding the demand-driven mechanism, we further examine whether farmers' decreased demand for P2P loans is due to their switch to traditional financing. We argue this is not the case during the COVID-19 outbreak. Traditional banks, mainly relying on a face-to-face interview to review borrowers' credit qualifications, encountered difficulties because of the lockdown policy and thus only granted loans to farmers who already had the bank's credit history.[13] Those who were precluded from banks before the pandemic could not obtain traditional financing after the crisis.

As no official aggregate bank-farmer lending data has been available during the pandemic yet, we provide evidence by the Enterprise Survey for Innovation and Entrepreneurship in China (ESIEC). The ESIEC was conducted by Peking University and surveyed 2,508 firms in May 2020, which is randomly selected from the Bureau of Industry and Commerce records. Among the sample firms, there are 198 agriculture-related firms, and 66% of them are small agriculture firms (less than ten employees).

This survey shows that approximately 88% of agriculture-related firms admitted that they did not enjoy any financial support from the government or banks during the pandemic, and 90% of the small agriculture firms denied receiving any financial support.[14] Hence, we rule out the possibility that the observed decline in farmers' P2P loans is the mechanical result of easing traditional financing. Thus, we conclude that the P2P platform did function as an alternative financing channel during the COVID-19 crisis, though the demand shrinkage dominates the supply.

5.3 The Impact of the Lockdown Policy

Unlike financial crisis or natural disaster, during which the transportation and logistics are little (or temporarily) affected, the COVID-19 crisis is first characterized by the province-wide compulsory lockdown policy. Previous literature has argued that transportation regulations and costs could significantly impact rural development and agricultural profits (Johnson, 1981; Roehner, 1996). In this section, we investigate whether the lockdown policy brings additional novel implications on farmers' P2P financing. Suggested by *Proposition 2* in our theoretical framework, the transportation delay or

[13] Agricultural Bank of China (ABC), for instance, approved loans to farmers with ABC's debit account or having a mortgage with ABC.

[14] Financial supports include low-interest loans, extended loan terms, and debt relief.

disruption would increase farmers' production costs and inhibit their microfinancing needs. To empirically test this proposition, we re-estimate Eq.(4.1) using the natural logarithm of the province's logistics capacity (*Logistics*) as the continuous treatment.

Column (1) of Table 3 reports the full sample result. There is a statistically significant decrease in loan amount in provinces with relatively high logistics capacities, with an elasticity of -0.147 (i.e., a one percentage change in freight turnover would result in a -0.147 percentage change in the P2P loan amount). To associate this result with the intensity of the lockdown policy, we dichotomize all provinces into high- and low-affected regions based on the median of death proportion, as the government implemented a longer and stricter lockdown policy in areas with more death cases. We find a statistically significant decline in the loan amount in the high-affected region (Column 2), while no significant change in the low-affected area (Column 3). Hence, the lockdown policy would impact farmers' microfinancing more in provinces with higher transportation capacities.

Table 3: The Impact of Lockdown Policy on Farmers' P2P Loans

Variables	(1) Full Sample Ln(Amount)	(2) High Death Ln(Amount)	(3) Low Death Ln(Amount)
Post $\times$ Ln(Logistics)	-0.147** (0.064)	-0.176** (0.065)	-0.064 (0.115)
Constant	11.112*** (0.080)	11.163*** (0.090)	11.005*** (0.126)
Month $\times$ Year FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Individual Characteristics	Yes	Yes	Yes
Observations	1,074	605	469
R-squared	0.100	0.128	0.086

Notes: The dependent variable is the natural logarithm of a P2P loan amount of borrower i in month year t. Post_t is a dummy variable that equals one if the loan is made after the *Wuhan lockdown* (i.e., January 23, 2020) and zero otherwise. Ln(Logistics) is the natural logarithm of the province's logistics capacity. Column (1) is based on full sample and Columns (2)-(3) are based on high-affected region and low-affected region, respectively. Standard errors, clustered at the province level, are shown in brackets. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

5.4 Aggregate-Level Implications

To verify the credit implications at the extensive margin, we extend our analysis to the province level by aggregating the number of loans in each province at the bi-month year level.[15]

Table 4: The Aggregate Impact of the COVID-19 on Farmers' P2P Loans

Variables	(1) Full sample Total No.	(2) Full sample Total No.	(3) Full sample Total No.	(4) High Death Total No.	(5) Low Death Total No.
Post × Hubei	-22.325***				
	(2.190)				
Post × Death		-22.992***			
		(2.261)			
Post × Ln(Logistics)			-6.723***	-9.513*	-5.130***
			(2.175)	(4.500)	(1.117)
Constant	13.317***	13.327***	25.777***	32.490***	21.427***
	(0.052)	(0.053)	(4.204)	(8.865)	(2.113)
Month × Year FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Observations	84	84	84	44	40
R-squared	0.844	0.844	0.849	0.880	0.795

Notes: The dependent variable is the total number of loans in each province at the bi-month year level. Post_t is a dummy variable that equals one if the loan is made after the *Wuhan lockdown* (i.e., January 23, 2020) and zero otherwise. Hubei_i is a dummy variable that equals one if borrower i is from Hubei province and zero otherwise. Death is a continuous measure for the pandemic severity, defined as the total provincial death cases scaled by the national sum as of April 7, 2020. Ln(Logistics) is the natural logarithm of the province's logistics capacity. Columns (1)-(3) are based on full sample and Columns (4)-(5) are based on high-affected region and low-affected region, respectively. Standard errors, clustered at the province level, are shown in brackets. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Column (1) of Table 4 shows that the aggregate Hubei loans dropped by 23 deals compared to other provinces after the COVID-19 outbreak. The same conclusion is drawn if we use the provincial death proportion (Column 2). Similar to the deal-level findings, provinces with larger logistics capacities suffered more losses in P2P loan deals during the

[15] As our sample period starts from January 23 and ends on April 7 in 2019 and 2020 respectively, we combine the January and February observations and March and April observations to avoid too few samples in January and April.

pandemic (Column 3). The negative effects in total loans are significant in both high- and low-affected regions (Columns 4 and 5), but the point estimate in the more pandemic-affected area is almost twice that of the less-affected area.

Though qualitatively similar, the aggregate-level point estimates are quantitatively more substantial than the deal-level results, presumably because the deal-level estimates are conditional on the initiation of P2P deals. Such a notable difference between the intensive and extensive margin further supports our demand-driven mechanism.

6 Conclusion

Small businesses are severely affected by the COVID-19 pandemic, confronting increased difficulties in accessing traditional financing. Although small business owners may want to resort to Fintech lending, investors' credit supply could also contract in crises. Thus, the dominant force in equilibrium Fintech loans is an intriguing and yet unexamined research question.

This paper is among the first to investigate small business owners' Fintech borrowings during the COVID-19 crisis through the lens of the agriculture sector. Using a matched transaction-level farmer-specific P2P loan data, we find that Chinese farmers from the most pandemic-affected region, Hubei province, substantially reduced their P2P loans relative to those from other areas after the crisis. Moreover, the COVID-specific lockdown policy also inhibited the Fintech credit, and the inhibition was more pronounced in the pandemic-affected region. We argue that the reduction in equilibrium loan is dominated by the contraction in demand rather than in supply, not driven by farmers' switch to traditional financing.

Our theoretical framework further disentangles the propagation mechanism of borrowing shrinkage in response to a crisis. Intuitively, when the aggregate demand is depressed due to the pandemic, farmers will inhibit production, lower working capital demand, and thus suppress borrowing needs. And when transportation is disrupted due to lockdown policy, farmers face higher production costs and thus reduce borrowings.

In light of the results, we do not find strong evidence that alternative financing channels did not function well during the crisis periods. Fintech credit supply might decrease, but our evidence shows an even more potent inhibition from small business owners' demand.

Following Appiah-Otoo (2020) that the Chinese government provides domestic credit to the private sector after the pandemic outbreak, our study develops policy recommendations along this line. We suggest that the state-owned banks consider providing more credit support for farmers, especially those from pandemic-affected regions and areas with larger logistics capacities. It is worth pointing out that our study generates a partial picture of Chinese farmers' credit responses to the COVID-19 via an online P2P lending platform, and future work could concentrate on their informal credit (i.e., borrowing from friends and relatives).

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Appendix Table I: Variable Definitions

Variables	Definitions
Amount	The amount that a farmer borrows in a P2P loan.
Interest Rate	The interest rate of the P2P loan.
Female	Dummy variable that equals one if the borrower is a female and zero otherwise.
House Ownership	Dummy variable that equals one if the borrower has home ownership and zero otherwise.
Salary	Borrower's annual income level: n=0, if less than 120,000 RMB; n=1, if between 120,000 and 240,000 RMB; n=2, if above 240,00 RMB.
Previous P2P Loans	Dummy variable that equals one if the borrower has experience in P2P loans.
Age	The borrower's age.
Education	Borrower's education level: n=1, if junior middle school and below; n=1, if high school; n=2, if college.
Marital Status	Dummy variable that equals one if the borrower is married.
Working Experience	Borrower's working experience: n=0, if from 0 to 3 years; n=1, if from 3 to 5 years; n=2, if more than 5 years.
Logistics	A province's latest freight turnover (i.e., year 2018).

Appendix Table II: Summary Statistics: The COVID-19 Cases and Aggregate Loans

Province	Confirm Cases	Death Cases	Number of Loans
Anhui	991	6	8
Chongqing	579	6	10
Fujian	355	1	49
Gansu	139	2	14
Hebei	328	6	143
Heilongjiang	892	13	45
Henan	1276	22	97
Hubei	68128	4512	187
Hunan	1019	4	20
Jiangsu	653	0	39
Jiangxi	937	1	41
Jilin	102	1	22
Liaoning	146	2	57
Neimenggu	193	1	121
Ningxia	75	0	12
Shaanxi	256	3	48
Shandong	787	7	36
Shanxi	197	0	28
Sichuan	561	3	8
Tianjin	189	3	3
Zhejiang	1268	1	86

Appendix Table III: Parallel Trend Test

Variables	(1) Ln(Amount)
Hubei × January 2019	0.058 (0.095)
Hubei × February 2019	0.103 (0.109)
Hubei × March 2019	-0.223 (0.173)
Constant	10.882*** (0.014)
Month × Year FE	Yes
Province FE	Yes
Individual Characteristics	Yes
Observations	752
R-squared	0.099

Notes: Standard errors, clustered at the province level, are shown in brackets. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.