FINTECH AND INFORMATION ASYMMETRY REDUCTION: HOW FINANCIAL TECHNOLOGY INNOVATION IS INCREASING THE RISK PROFILE OF RURAL COMMUNITY BANKS

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FINTECH AND INFORMATION ASYMMETRY REDUCTION: HOW FINANCIAL TECHNOLOGY INNOVATION IS INCREASING THE RISK PROFILE OF RURAL COMMUNITY BANKS

Research in Progress

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Abstract

Finance literature has frequently cited information asymmetry advantages of community banks due to their relationship banking orientation; however, financial technology firms (FinTechs) are beginning to leverage alternative data sources that may be eroding these advantages. Moreover, with increasing internet availability and the streamlined web-based credit application processes employed by FinTechs, community banks in rural markets may also be losing their proximity advantages. By analysing 5,852 community banks from 2012 to 2017 and drawing on information asymmetry and prospect theories, we hypothesize and find support for the idea that increasing competitive pressure from FinTechs elevates the risk profile of community banks in rural markets. In addition to providing theoretical insights on the implication of FinTechs on the United States banking system, these findings may be fruitful for policymakers and suggest the need for small, rural banks to embrace FinTech partnerships as part of their operating strategy.

Keywords: information asymmetry, community banks, customer orientation, fintech

1 Introduction

Large bank brands are often the first to come to mind when reflecting on the banking industry; however, community banks actually represent over 90 percent of all bank charters in the United States. In many rural communities, they are the only local option, given that larger banks may not find it economically feasible to operate within small markets (FDIC 2014). Community banks have a long history of relationship lending and are known for supporting their communities by providing funding to small and medium-sized businesses and consumer credits. Given the size of their customer base, the proximity to their customers, and their geographic orientation to non-metropolitan areas, community banks are thought to have a richer knowledge of their customers’ character and unique circumstances, which has been collectively referred to as “soft information.” Soft information is an essential data element as it is believed to be a factor in enabling the extension of credit to customers who may not otherwise qualify for a loan when only considering hard information (e.g., credit scores, loan-to-value, and debt-service-coverage) alone. Additionally, their relationship orientation allows for community banks to tailor loan underwriting to the customer’s needs rather than forcing the customer to choose between “cookie-cutter” lending products. Unfortunately, irrespective of the vital role in the U.S. economy, the ongoing viability of the community bank business model is in question.
While still representing most bank charters, community banks with under $500 million in total assets have declined in volume by about 70 percent, or 7,600 institutions, between 1990 and 2019 (Bostic 2020). The FDIC’s 2014 Community Banking Study lists several potential factors for this decline. For one thing, as some of these institutions have grown, they have naturally migrated into larger bank size categories; however, this does not account for the substantial decline in total bank charters that has also been observed over the period. Most charter reduction is attributed to consolidations outpacing new entrants into the market, although some bank failures have also occurred, particularly during times of economic distress. Reasons for consolidations include economies of scale, entry into new markets, rural market depopulation, increasing business costs, complying with regulation, and succession concerns (FDIC 2014). Regardless of the reason, there is considerable apprehension about who will help to fill the void left by these institutions should the number of community banks continue to shrink.

Funded by considerable venture capital investment and supported by highly skilled developers, FinTechs have brought substantial innovation into the financial services sector within a very short period. Although their products are expanding, FinTechs have thus far heavily targeted small consumer lending, small business loans, and some mortgage origination. FinTechs have disrupted the financial services sector by changing the dynamics of lending in several ways. First, FinTechs are harvesting previously untapped data sources during underwriting, particularly in the consumer credit space, enabling them to take advantage of soft credit factors in underwriting that banks have not traditionally considered. Second, FinTechs have created more diverse credit products that are more tailored to the unique needs of borrowers, providing a better fit between product and customer. Third, FinTechs have extended product reach through easy-to-use online channels, removing geographic barriers to customers and products. Last, FinTechs have streamlined the loan application process for customers and the speed of loan processing, making their product offerings more appealing (Gomber et al. 2018). While these innovations have competitive implications for all banking institutions, they appear to directly undermine many of the competitive advantages of community banks operating in rural markets.

One could surmise that FinTech borrowers, particularly those residing in rural areas, may have different characteristics from non-FinTech borrowers. If that is the case, their migration out of community banks and into FinTech lenders would likely change the residual composition of the community bank borrower pool. Maggio and Yao (2020) found that FinTech lenders begin by targeting less creditworthy individuals to build market share and then expand to better borrowers over time. Additionally, although they found that FinTech lenders, on average, charge higher rates than traditional banks, they charge lower rates to higher-quality borrowers. Furthermore, they also found that FinTech borrowers have higher default rates, suggesting that FinTechs are lending to weaker borrowers. However, the increased rate of default is not necessarily a function of poverty but may be driven by a propensity to spend, we suggest that the evidence corroborates this view in part. In that sense, it may be that affluent individuals are the customers with the greatest access to technology along with the sophistication to use the devices necessary to connect them to FinTech firms. Yet, despite their affluence, their propensity to spend may result in a borrowing ceiling from more conservative community banks, drawing them into the hands of FinTech lenders that can more effectively price to risk. Therefore, FinTechs may capture more affluent customers, causing deterioration in the residual lending base available to community banks as these affluent borrowers migrate out of their borrower base. Moreover, the authors of this study found that these borrowers have a high degree of loyalty to the FinTech lenders, resulting in a sustained shift away from their tendency to borrow from traditional banks.

In this study, we will examine whether the infusion of FinTech lending into banking markets has changed the credit risk characteristics of community banks. To answer this question, we examine the context of LendingClub, a large FinTech lender, to look specifically at how LendingClub loans have impacted bank lending concentrations and non-performing assets using a panel of 5,852 community banks across the United States, from 2012 to 2017. Consistent with information asymmetry and prospect theories, we find a correlation between increased FinTech lending activity in the local market and bank credit concentrations, as well as non-performing asset levels in small rural community banks.
The remaining parts of the study are structured as follows: Section 2 – Theoretical Background and Hypotheses, Section 3 – Method, Section 4 – Limitations, Section 5 – Discussion and Conclusion.

2 Theoretical Background and Hypotheses

2.1 Theoretical Background

Information asymmetry theory plays a significant role in the market dynamics of the U.S. banking system. Although most known for describing information asymmetry in the used car market, the seminal paper (Akerlof 1970) addresses a number of other industries and touches upon how local moneylenders had certain advantages over banks in central cities. Specifically, local moneylenders were charging significantly higher rates of interest than larger banks. However, they were still able to attract customers in rural markets because the local moneylenders could enforce contracts more effectively and possessed “personal knowledge of the character of the borrower” (Akerlof 1970). Similarly, community banks tend to operate in close geographic proximity to their customers, develop richer information about a customer’s character and circumstances, and interact with clients more intimately. However, anecdotal evidence indicates the innovative technologies employed by FinTech firms are reducing this information asymmetry-based competitive advantages in ways larger, out-of-territory banks have not managed. FinTechs are tapping into previously unused data sources in analysing borrowers, improving the customer-credit fit with better tailoring options, removing geographic barriers through online origination channels, and increasing underwriting speed (Gomber et al. 2018).

In addition, as suggested by prospect theory, individuals avoid risk when their current situation or prospects are positive and seek risk when their current situation or prospects are negative (Kahneman and Tversky 1984). In some ways, consumer regulation has been designed to restrict desperation credit to protect borrowers from predatory terms, but at the same time, their situation and prospects remain unchanged. If they are unable to obtain credit from traditional institutions, it may force them to look to unconventional creditors. Such creditors offer higher cost credit products such as those offered by less regulated FinTech lenders with the ability to effectively price the risk.

In rural communities, it is possible that this phenomenon could be resulting in a migration of affluent customers with a high propensity to spend out of banks and into FinTechs. Technologically savvy individuals with access to computers and mobile devices should have the highest accessibility to credit obtained through the digital channels provided by FinTech firms. Further, technological access and skills tend to be associated with affluence; however, despite having high incomes, a high propensity to spend may still drive affluent customers to seek additional credit beyond what they can access through conservative and tightly regulated community banks. With the advent of FinTech lending, these individuals have become less restricted from borrowing because of this alternative channel potentially driving them away from traditional banking institutions and into the hands of FinTech lenders. As a result, there could be a shift in the customer characteristics of community bank borrowers that could be impacting the risk profile of community banks as they lose access to affluent customers who want to exceed the credit limitations that they have been subject to within the banking system. In effect, this could leave community banks with a smaller share of affluent customers with a tendency to borrow, leaving community banks with less affluent customers and affluent customers with a low tendency to borrow.

2.2 Prior Work

Two recent studies compared FinTech and traditional bank lending. First, Jagtiani and Lemieux (2018) analysed how effective LendingClub was meeting under-served borrowers’ needs relative to large banks who are the predominant issuers of credit cards. LendingClub has penetrated some under-served communities, better than large banks. These include highly concentrated markets, areas with fewer local branches, and economically distressed localities by leveraging soft information that traditional banks had not considered. Jagtiani and Lemieux (2018)’s comparison between FinTech consumer lending and large bank credit card lending is a sensible. Credit card lending is the most active source of unsecured
small dollar credit offered by banks to consumers. LendingClub is also used as a credit mechanism for small business owners, a key market demographic of community banks. Given that community banks have historically met the needs of small business borrowers in large part because of information asymmetry advantages over larger banks, the ability of FinTech lenders, like LendingClub, to reduce these asymmetries raises questions as to the resulting impact these entities will have on community bank lending.

Second, in comparing the competitiveness of FinTechs against community banks, Balyuk, Berger, and Hackney (2020) looked at small business lending, which is the most significant business line of community banks today. They found that FinTech lenders tended to “replace loans by large/out-of-market banks more than small/in-market banks” because FinTechs were better equipped for “more efficient processing of hard information, rather than the hardening of soft information.” This would imply that community banks may still have an information edge at least in business banking; however, like the Jagtiani and Lemieux article suggests, FinTechs have harnessed previously untapped data sources in the consumer space and, at some point that may extend to the business space. The Balyuk, Berger, and Hackney (2020) paper also finds support for FinTech lenders targeting riskier small business clients than what large, out-of-market banks are pursuing. However, it is unclear how FinTech competition is collectively impacting community bank lending portfolio risk, particularly in rural markets where community banks are already dealing with a multitude of challenges.

2.3 Hypotheses

Since community banks in rural markets have historically operated with limited local market competition and proximity to their customer base, these types of banks have benefited most from information asymmetry advantages. Not only are customers more inclined to shop for credit locally, these entities also benefit from the knowledge of the local market and customer character, including willingness to repay, integrity, and employment stability. Such factors are often lesser-known to out-of-territory institutions. However, given that FinTechs have broken geographic barriers through the use of intuitive online lending platforms, have increased the speed of underwriting, and are leveraging non-traditional underwriting criteria, proximity and soft-information benefits are eroding, weakening the competitive advantage of rural banks significantly. Given that FinTechs are mostly targeting small business and consumer lending, rural banks are likely to have less opportunity to diversify credit risk across a wider portfolio of lending products (Amery 2020). Further, the increased likelihood of FinTechs attracting technologically sophisticated individuals suggests that more affluent borrowers with a high propensity to spend are most likely to seek FinTech lending, causing a migration of wealthier, loan-seeking customers away from community banks. Given these factors, we hypothesize that:

**Hypothesis 1a:** An increase in FinTech lending will be positively associated with increased lending concentrations at community banks operating in rural markets.

**Hypothesis 1b:** An increase in FinTech lending will be positively associated with increased non-performing asset exposure at community banks operating in rural markets.

Larger financial institutions typically have more sizeable branching networks, more sophisticated online transaction capabilities, and more diverse product lines. Therefore, losing some consumers and small business lending should be less impactful given that they have a wider array of products that can be used for diversification. Furthermore, even if headquartered in rural communities, larger banks should be less susceptible since they have more opportunity to diversify their credit portfolio by accessing customers outside of their headquarters’ geographic boundary. Given these factors, we hypothesize that:

**Hypothesis 2a:** An increase in FinTech lending will be negatively associated with increased lending concentrations as bank asset size increases.

**Hypothesis 2b:** An increase in FinTech lending will be negatively associated with increased non-performing asset exposure as bank asset size increases.
3 Method

3.1 Data and Variables

We collected banking data from required regulatory financial data disclosures published in the Federal Financial Institution Examination Council (FFIEC) Call Reports from 2012 to 2017, a period of stability and economic growth in the United States. Because our interest was in the impact on community banks, the sample was limited to banks with total assets of approximately $10 billion or less in line with regulatory definitions. FinTech lending was limited to LendingClub data, which the company releases at the three-digit zip code level to protect borrower anonymity. This data also spanned from 2012 to 2017. To convert the LendingClub data to county-level, a weighted averaging method was employed using the population data from the 2010 U.S. Census. Branch data by county and bank age were obtained from the Federal Deposit Insurance Corporation (FDIC). Last, the county-level percentage of the population below the poverty level was obtained from the American Community Survey conducted by the U.S. Census.

We used two measures of credit risk as the dependent variables in our regression analysis. First, we calculated the Herfindahl-Hirschman Index (HHI) of each bank’s loan portfolio as a measure of how concentrated their loans were across loan categories. The idea is that higher credit concentration results in higher credit risk to the bank due to lack of diversification should a particular credit sector experience a systemic downturn. The HHI measure is commonly used to measure industry concentration for merger and acquisition analysis, but has been applied to measuring lending concentrations as used in Skrulytė and Freitakas (2012). Secondly, the Texas ratio was calculated as a measure of a bank’s non-performing assets relative to capital and the loan loss reserve. Therefore, a higher Texas ratio is indicative of more credit risk because of either elevated problem assets or a decline in loss protecting capital and reserves. The Texas ratio is a well-established credit risk metric used by United States banking regulators to measure problem assets exposure. The independent variables of interest include the county-level volume of FinTech lending, asset size, a rural market indicator, and the interaction between these variables. Bank asset size and FinTech lending volume were log-transformed and mean-centered.

Control variables include bank age, return on average assets, Tier 1 leverage ratio, branches per capita, and county poverty rate. First, we control for bank age to account for experience, product build-out, and customer relationship advantages of established banks. Second, we control for return on average assets and Tier 1 leverage ratio since profitability and capital strength serve as proxies for bank financial strength. Third, we control for branch access since a heavily branched market is indicative of traditional banking competition, which could be another possible factor in banks having to resort to increasing credit risk in their loan portfolios. Last, we control county poverty because of the possibility that impoverished localities may reduce the lending opportunities of community banks. ROAA, Tier1 leverage ratio and branches per capita were scaled by 1,000.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
<th>Citations</th>
</tr>
</thead>
<tbody>
<tr>
<td>HHILP</td>
<td>Herfindahl-Hirschman Index of the bank’s loan portfolio, reflecting on overall concentration across loan categories.</td>
<td>Skrulytė and Freitakas (2012) Calculated from FFIEC data</td>
</tr>
<tr>
<td>TXRAT</td>
<td>The bank’s Texas ratio, reflecting on credit troubles and is measured as non-performing assets divided by tangible capital plus loan loss reserves.</td>
<td>Siems (2012) Calculated from FFIEC data</td>
</tr>
<tr>
<td>CFLV</td>
<td>The volume of outstanding lending tree loans in the county served by the FinTech firm.</td>
<td>Jagtiani and Lemieux (2018)</td>
</tr>
<tr>
<td>ASSET</td>
<td>The asset size of the bank in thousands of dollars.</td>
<td>FFIEC Data</td>
</tr>
<tr>
<td>AGE</td>
<td>The age of the bank in the number of years since its founding year.</td>
<td>FDIC Statistics on depository institutions</td>
</tr>
<tr>
<td>ROA</td>
<td>The bank’s net income as a percentage of its average total assets for the year.</td>
<td>FFIEC Data</td>
</tr>
</tbody>
</table>
A bank’s core capital is divided by its average assets in the year.  

Branches per capita in a county, i.e., total bank branches/county’s population.  

A 5-year estimate of population below the poverty level in the county.  

Binary variable indicating whether the bank is headquartered in a rural area.  

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>LEV1</td>
<td>A bank’s core capital is divided by its average assets in the year.</td>
</tr>
<tr>
<td>BRAN</td>
<td>Branches per capita in a county, i.e., total bank branches/county’s population.</td>
</tr>
<tr>
<td>CPR</td>
<td>A 5-year estimate of population below the poverty level in the county.</td>
</tr>
<tr>
<td>RURAL</td>
<td>Binary variable indicating whether the bank is headquartered in a rural area.</td>
</tr>
</tbody>
</table>

**Table 1. Description of Variables**

### 3.2 Empirical Model

Since our dataset consisted of longitudinal panel data, we employed two fixed effects regression models to control possible invariant unobserved firm characteristics that could be correlated with observed explanatory variables (Woolridge 2016). The general model specification is:

\[ Y_{it} = \beta_1 X_{1,it} + \cdots + \beta_k X_{k,it} + \alpha_i + u_{it} \]

Where the dependent variable Y represents the HHI of each bank’s loan portfolio for a given year in the first regression, and the Texas ratio, or a measure of non-performing assets as a percentage of capital and loan loss reserves, of each bank for a given year in the second regression; X represents a vector of factors of interest including FinTech loan volume, bank size, and rurality, as well as control variables; \( \beta \) is a vector of parameters to be estimated; and \( \alpha \) represents the entity-specific intercepts capturing the unobserved heterogeneity across firms and \( u \) is the idiosyncratic, or time-varying error (Woolridge 2016). In addition to the twelve core parameters being estimated, an autoregressive component at t-1 was incorporated into each model to reflect that both current concentration and credit risk are dependent on their historical values. In other words, a financial institution that recently reported a high concentration to certain lending sectors or that reported high exposure to problem assets would likely continue to be exposed in the coming year due to the strategic changes that must be made to alter the state of the balance sheet, as well as the time involved to enact such changes.

Specifically, we used the following model specifications to test our four hypotheses by looking at the interactions between local FinTech lending volume, bank size, and rurality.

**HHLP**

\[ HHLP = \beta_1 \text{CFLV}_{it} + \beta_2 \text{ASSET}_{it} + \beta_3 \text{RURAL}_{it} + \beta_4 \text{CFLV}_{it} \times \text{RURAL}_{it} + \beta_5 \text{ASSET}_{it} \times \text{RURAL}_{it} + \beta_6 \text{CFLV}_{it} \times \text{ASSET}_{it} + \beta_7 \text{CFLV}_{it} \times \text{RURAL}_{it} \times \text{ASSET}_{it} + \beta_8 \text{CFLV}_{it} \times \text{ASSET}_{it} \times \text{RURAL}_{it} \times \text{ASSET}_{it} + \beta_9 \text{AGE}_{it} + \beta_{10} \text{ROA}_{it} + \beta_{11} \text{LEV1}_{it} + \beta_{12} \text{BRAN}_{it} + \beta_{13} \text{CPR}_{it} + \alpha_i + u_{it} \]

**TXRAT**

\[ TXRAT = \beta_1 \text{CFLV}_{it} + \beta_2 \text{ASSET}_{it} + \beta_3 \text{RURAL}_{it} + \beta_4 \text{CFLV}_{it} \times \text{RURAL}_{it} + \beta_5 \text{ASSET}_{it} \times \text{RURAL}_{it} + \beta_6 \text{CFLV}_{it} \times \text{ASSET}_{it} + \beta_7 \text{CFLV}_{it} \times \text{RURAL}_{it} \times \text{ASSET}_{it} + \beta_8 \text{CFLV}_{it} \times \text{ASSET}_{it} \times \text{RURAL}_{it} \times \text{ASSET}_{it} + \beta_9 \text{AGE}_{it} + \beta_{10} \text{ROA}_{it} + \beta_{11} \text{LEV1}_{it} + \beta_{12} \text{BRAN}_{it} + \beta_{13} \text{CPR}_{it} + \alpha_i + u_{it} \]

### 3.3 Results

Regression results are presented in Table 2. In our first model, which analyses the influence of local FinTech lending volume on the HHI, or degree of concentration, of community bank lending portfolios, an inverse relationship is indicated between FinTech lending volume in the local market and the HHI of community bank lending portfolios (\( \beta=-6.920, p<0.1 \)). However, when looking at the impact of the interaction between local FinTech lending volume and the rural indicator on community bank lending concentrations, we observe a positive association (\( \beta=10.359, p<0.1 \)), providing some support for Hypothesis 1a. Although these relationships are not particularly strong in terms of significance, they still suggest that community banks operating within rural areas have a higher degree of exposure to concentration risk as FinTech lenders enter the market. Bank size, however, seems to be a more pronounced factor. Both bank size (\( \beta=-51.646, p<0.01 \)) and the three-way interaction of bank size, local
FinTech lending volume, and the rural indicator variable (β=-14.743, p<0.01) have statistically significant negative relationships with the HHI of community bank lending portfolios supporting Hypothesis 2a. From these relationships, we can surmise that larger community banks have diversification advantages that enable them to continue to lend to various sectors despite the inflow of FinTech competition. In contrast, smaller community banks operating in rural markets are less resilient to FinTech entrants penetrating their previously close-knit markets. The control variables also present some interesting observations. First, the regression results show that banks with higher leverage capital tend to be more highly concentrated (β=0.452, p<0.05), which could be because they are having difficulty deploying capital due to limited lending opportunities or that they are choosing to hold back capital as a risk management response to the concentration risk. However, the negative relationship between return on assets and concentration risk (β=-1.574, p<0.01) may suggest the former.

In our second model analysing the influence of local FinTech lending volume on community bank Texas ratios, or nonperforming asset exposure, we observe that local FinTech lending volume is associated with a reduction in community bank Texas ratios (β=-0.047, p=0.001). This result provides some support for the idea that FinTechs primarily target “bottom-feeder” loans with elevated credit risk, consistent with Prospect Theory. However, like observed in the first model, when interacted with the rural indicator variable, we observe a positive and significant relationship with the Texas ratio (β=0.062, p=0.001). This result indicates FinTech lending may be driving community banks in rural markets to take on additional credit risk, supporting Hypothesis 1b. Community rural banks may not have as much of an information asymmetry advantage relative to FinTech lenders. On the other hand, larger banks (β=1.50, p=0.001) are correlated with increased problem credit exposure, whereas rural banks (β=-3.87, p=0.001) have an inverse relationship, highlighting potential information asymmetry advantages historically exhibited by smaller institutions operating in close-knit communities. Although there is a negative and statistically significant relationship between the interaction effect of local FinTech lending volume and bank asset size (β=-0.022, p=0.001), we do not observe a statistically significant relationship with the three-way interaction term incorporating the rural indicator variable (β=-0.012), so we find only partial support for Hypothesis 2b. This time, we find evidence that increased traditional competition, as evidenced by a higher density of local branches (β=-0.059, p=0.01), is associated with higher credit risk. Last, and as expected, more mature banks (β=-0.060, p=0.001), with higher capital (β=-0.002, p=0.001), and better earnings (β=-0.032, p=0.001) tend to have lower exposure to problem assets.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Fixed Effects (bank, year)</th>
<th>(2) Fixed Effects (bank, year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CFLV</td>
<td>-6.920#</td>
<td>-0.047***</td>
</tr>
<tr>
<td>ASSET</td>
<td>-51.646 **</td>
<td>0.150***</td>
</tr>
<tr>
<td>RURAL</td>
<td>-3.479</td>
<td>-0.387**</td>
</tr>
<tr>
<td>CFLV × RURAL</td>
<td>10.359#</td>
<td>0.062***</td>
</tr>
<tr>
<td>ASSET × RURAL</td>
<td>1.479</td>
<td>-0.059</td>
</tr>
<tr>
<td>CFLV × ASSET</td>
<td>1.718</td>
<td>-0.022***</td>
</tr>
<tr>
<td>CFLV × RURAL × ASSET</td>
<td>-14.743** (4.560)</td>
<td>-0.012 (0.006)</td>
</tr>
<tr>
<td>AGE</td>
<td>2.713</td>
<td>-0.060***</td>
</tr>
<tr>
<td>ROA</td>
<td>-1.574**</td>
<td>-0.032***</td>
</tr>
<tr>
<td>LEV1</td>
<td>0.452*</td>
<td>-0.002**</td>
</tr>
<tr>
<td>BRAN</td>
<td>5.920</td>
<td>0.059**</td>
</tr>
<tr>
<td>CPR</td>
<td>-4.706**</td>
<td>-0.002</td>
</tr>
<tr>
<td>LAG 1</td>
<td>0.465***</td>
<td>3.996***</td>
</tr>
<tr>
<td>R-Squared</td>
<td>33.55%</td>
<td>22.50%</td>
</tr>
</tbody>
</table>

Note: Standard errors in parentheses. *** p<.001, ** p<.01, * p<.05, # p<.1

Table 2. Preliminary Results
4 Limitations

There are a few limitations in our study. Most importantly, FinTech lending data was limited to loans from LendingClub, so we are unable to account for FinTech lending from other providers. We assume that LendingClub serves as a good proxy for each county’s use of FinTech lending since it is a major FinTech lender within the United States; however, it is possible that different FinTech lenders market to alternative geographic locations. Additionally, it is likely that FinTech lenders cater to particular loan categories and that using only a single FinTech lender may not accurately depict the full market implications they are collectively having on communities. For example, if a FinTech lender specializes in agricultural loans, the influx of FinTech funding on a farming community may be under-represented in our data set. Last, LendingClub data was only available to the three-digit zip code level so weighted averaging had to be applied to approximate county-level data. Misallocations due to this estimating could potentially impact the results of the study.

5 Discussion and Conclusion

In this study, we consider the implication of information asymmetry and prospect theories in the context of the emergence of FinTech lending in community banking markets. We find evidence that the influx of FinTech lending has resulted in an increased credit risk profile for small, community banks operating in rural markets. Many of the technological advances brought to market by FinTech lenders most directly challenge these entities. Additionally, because of the likelihood of FinTech lenders attracting affluent, credit-seeking customers, there may be a systemic shift in the borrower composition of rural, community banks that may cause long-term challenges for these institutions. As we continue to work on this project, we plan to consider additional risk dimensions and further refining the tie to information systems theory.
References


