The impact of Fintech on employment

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Abstract

We investigate the relationship between online lending and employment change. Using unique loan-level data, we find that online lending is positively associated with job destruction and negatively associated with job creation and replacement hires. These results are robust to endogeneity tests, including a quasi-natural experiment relating to state regulatory approval and an instrumental variable approach relating to changes in debt-to-income policy of a large online platform, Lending Club. Furthermore, we show evidence that financial overextension and low creditworthiness amplify the negative effects of online loans on employment change. Overall, our findings suggest a potential dark side of how emerging peer-to-peer platforms influence labor markets and economic outcomes.

JEL classification: G21, G18, G28, L21

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1. Introduction

The rapid rise of Fintech has transformed the lending landscape, giving birth to innovative online models such as peer-to-peer lending platforms (Nowak et al., 2018; Rau, 2020). By directly connecting lenders and borrowers, online lending has shown promise in overcoming financial barriers, offering higher returns for lenders along with more affordable credit for underserved segments (Milne and Parboteeah, 2016). With online platforms already capturing a sizable share of U.S. unsecured loan market as of 2018[1], a key question emerges on how this financial innovation might impact the real economy. Specifically, how does growing access to online loans affect employment change? We center our examination on employment change, given its important role in driving real economic development and maintaining social stability.

As an emerging lending market, the literature has taken an interest in examining factors that drive the success of online lending. One research stream focuses on the solvency of borrowers and loan purposes (Emeker et al., 2015; Railiene, 2018). Another examines the borrower's personal individual status like age (Gonzalez and Loureiro, 2014), gender (Chen et al., 2017), region (Burtch et al., 2014; Lin and Viswanathan, 2015), appearance (Duarte et al., 2012) and social relationship (Everett, 2015; Hildebrand et al., 2016). Recent research has expanded to explore the social implications of online lending by reducing barriers that limit access to capital, such as bankruptcy filings (Wang and Overby, 2017) and women's access to medical care (Ozer et al., 2023).

Parallel to the online lending literature, a large body of research in economics has investigated the relationship between employment dynamics and debt levels. A broad consensus has emerged, documenting that firms with substantial debt facing severe financial

[1] By 2018, online lending had already reached around one-third of the U.S market for unsecured personal or small business loans (Balyuk and Davydenko, 2019).

constraints tend to lay off workers more frequently (Campello et al., 2010; Giroud and Mueller, 2017). In a related vein, Caggese et al. (2016) and Benmelech et al. (2021) demonstrate that employment decisions are constrained by firms' financial health and liquidity. Financially constrained firms give more weight to current cash flows than to futures ones, and therefore decide on whom to fire on the basis of firing costs rather than considering expected productivity. However, despite this extensive research, there is scant evidence to date on whether an online lending market exerts an influence on employment dynamics.

We propose two competing hypotheses for the effect of online lending on employment change. On one hand, the investment hypothesis suggests that online lending can facilitate job upsizing by enhancing credit accessibility (Ozer et al., 2023), allowing borrowers to maintain their workforce during temporary downturns and potentially expand it through investments in positive NPV projects. This view posits that increased credit access can alleviate financial distress and stimulate small business growth. On the other hand, the downward spiral hypothesis proposes that online lending may lead to job downsizing. This perspective argues that easier access to loans might cause borrowers to take on unsustainable debt (Skiba and Tobacman; 2019), forcing them to lay off employees to manage costs and maintain credit access. Additionally, the potential for loans to be issued to unqualified borrowers due to less rigorous online assessments could result in business closures and employment reductions.

To test these competing hypotheses, our analysis centers on Lending Club (LC), the largest online lending platform in the United States, which we consider representative of other online lending platforms[2]. Our sample consists of county-level data over the period 2007 to 2020. To measure the potential impact of LC loans, we follow Wang and Overby (2022) and use loans outstanding per capita, defined as the total number of LC loans outstanding as a percentage of the county's population. We examine employment change through three distinct

[2] See, e.g., Bertsch et al., (2020)

measures: job destruction, which captures the existing job elimination; job creation, reflecting the generation of new employment opportunities; and replacement hires, indicating labor market churn beyond net job creation.

Our baseline panel regression results reveal that loans outstanding have a negative effect on all three employment dimensions we analyze, thus supporting the downward-spiral hypothesis. The economic significance is notable, with LC loans per capita associated with an average 2.5% decline in overall employment. These findings remain robust to various sensitivity tests, including alternative proxies for employment and controls for house price change and similar online lending platform.

To address potential endogeneity concerns, we implement two empirical approaches: a quasi-natural experiment and an instrumental variable (IV) approach. First, the quasi-natural experiment exploits the variation in state regulators' approval timing for loan issuance. This regulation serves as an exogenous shock to increase LC loans per capita in affected counties. Second, the IV approach utilizes the debt-to-income policy change enacted by LC in 2012, which tightened lending restrictions on borrowers, as an instrument for LC loans per capita, consistent with prior research (Wang and Overby, 2022). Both analyses corroborate our baseline results, suggesting a causal relationship between LC loans outstanding and negative employment effects.

We also perform additional tests to determine whether the negative impact of LC on employment can be attributed to borrower's debt trap or creditworthiness. Using debt expansion and the borrowers' debt-to-income ratios as proxies for the debt trap mechanism, we find the relationship is more pronounced when loans are used to expand overall debt and when borrowers exhibit high debt-to-income ratios. These findings suggest that LC loans may exacerbate financial strain for already indebted borrowers, potentially leading to a 'debt trap' scenario where increased debt servicing costs necessitate employment reductions. For the credit risk mechanism, we utilize the borrowers' credit scores and business life cycle stages as creditworthiness proxies. Our results indicate that the employment reduction associated with LC loans outstanding is more prominent for borrowers with low credit scores and for businesses in early life cycle stages. The results indicate that lower creditworthiness amplifies the negative employment effects of LC loans, underscoring the importance of robust credit risk assessment in online lending platforms.

To obtain further evidence on how online lending can destroy jobs, we examine the changes in borrower's default and bankruptcy filings with the change of LC loans outstanding. We find that LC loans that increase borrower's overall debts are positively associated with default and bankruptcy filings. These findings are consistent with the fact that the demand of LC loans exacerbate borrower's risk of default and bankruptcy filings, which results in a significant decrease in jobs.

Lastly, we examine how local socioeconomic conditions affect our results. Overall, we find a negative effect of LC loans outstanding on employment is more pronounced in counties with lower education levels, more widespread internet access, and less available banking services. These results suggest that the impact of expanded access to online lending on employment outcomes may be detrimental in vulnerable community with limited financial literacy and insufficient banking options.

Our study makes two significant contributions to the extant literature. Firstly, it augments the discourse on the costs and benefits of online lending platforms. Recent scholarship has illuminated their societal and economic impacts, including effects on capital access, funding-allocation efficiency, and household financial stability (Mollick and Robb, 2016; Butler et al., 2017; Wei and Lin, 2017; Wang and Overby, 2021; Ozer et al., 2022). We extend this line of inquiry by elucidating the potentially detrimental effects of online lending platforms on employment. Our findings suggest that a hitherto underexplored implicit cost of these platforms manifests in the form of increased debt service burden and compromised creditworthiness.

Secondly, our research contributes to the burgeoning literature examining the nexus between labor and finance. Prior studies have investigated the impact of various financial products and services, such as payday loans and credit cards, on household financial well-being and labor market outcomes (Campbell et al., 2008; Karlan and Zinman, 2010; Wilson et al., 2010; Carrell and Zinman, 2014). Concurrently, another strand of research has leveraged banking deregulation and banking relationships to explore the effects of increased bank credit supply on aggregate employment at firm or state levels (Hombert and Matray, 2016; Benmelech et al., 2021; Behr et al., 2022). Our study offers novel insights into the role of online lending platforms—specifically Lending Club—as a predictor of employment change. We present evidence suggesting that Lending Club's operations may exacerbate economic hardship and impede new job creation.

Our study also carries important practical implications. By quantifying the magnitude of employment losses associated with online lending platforms, we provide policymakers with empirical evidence to guide platform design and regulation, with the aim of achieving a balance between fostering financial innovation and safeguarding job growth. For practitioners, our findings underscore the importance of prudent credit assessment and responsible lending practices to mitigate the risk of exacerbating financial distress and its cascading effects on employment.

We structure the remainder of the paper as follows. Section 2 discusses the background and hypothesis development. Section 3 describes the data and provide the summary statistics. Section 4 and 5 report empirical results and additional analyses. Finally, Section 6 concludes the paper.

2. Background and Hypothesis Development

Online lending platforms are digital platforms that connect borrowers and lenders in the lending process. These platforms use an online interface to facilitate individuals or businesses to borrow from prospective lenders. The entire lending process, from application to disbursement, takes place on the platform without the need for traditional brick-and-mortar financial institutions. The convenience and speed of obtaining funds through these platforms have contributed to their growing popularity, with Yahoo Finance (2024) projecting a 12.7% growth rate for the United States online lending platforms market during 2024-2034.

This rapid growth is underpinned by the platforms' innovative use of financial technology to enhance efficiency and accessibility. By leveraging advanced pricing and underwriting systems, online lending platforms reduce information asymmetry and transaction costs (Balyuk, 2016; Philippon, 2016). For instance, these platforms employ algorithms to assess loan risks and assign grades to borrower requests using codifiable personal financial data. Research indicates that online lending could potentially substitute for conventional lending methods (Tang, 2019; Liu et al., 2020) and has successfully penetrated areas underserved by traditional banking markets (Jagtiani and Lemieux, 2019). Moreover, online lending platforms have been shown to help borrowers, even those with access to traditional capital, secure loans with attractive terms such as lower interest rates (Butler et al., 2017).

While the growth and potential benefits of online lending are evident, its impact on employment dynamics remains a subject of debate. Based on the extant literature, we propose two contrasting hypotheses that reflect potentially different outcomes. Namely, the investment hypothesis and downward spiral hypothesis.

The investment hypothesis posits that online lending facilitates job upsizing. By enhancing credit accessibility, it potentially enables borrowers to smooth wage expenditures during periods of income or consumption volatility (Wang and Overby, 2021; Ozer et al., 2023).

These entities can maintain their workforce during temporary downturns, avoiding layoffs that might otherwise be necessary to manage short-term financial constraints. Moreover, the increased credit access afforded by online lending can stimulate small business investment and indirectly foster job creation, given the complementarity between capital and labor. When firms leverage credit to invest in positive net present value (NPV) projects, they may expand their workforce to efficiently manage the additional capital. This process is crucial for firm survival and future performance enhancement. Thus, it predicts online lending may alleviate financial distress for borrowers, potentially leading to job upsizing.

In contrast, the downward spiral hypothesis suggests that online lending may precipitate job downsizing. First, enhanced loan accessibility might induce borrowers to assume more debt than they can sustainably manage, potentially trapping them in an onerous debt service cycle (Athreya et al., 2012; Narajabad, 2012; Livshits et al., 2016; Skiba and Tobacman; 2019). To avert loan acceleration and maintain credit access, small businesses may opt to resort to employee layoffs, thereby curtailing operating costs and assuaging lenders' concerns about future repayment capacity. The pressure to service debt may also lead businesses to forego growth opportunities or necessary investments, further stagnating employment growth. Second, online loans may be issued to unqualified borrowers who subsequently face repayment difficulties (Jagtiani and Lemieux, 2017; Kim and Hann, 2019). The ease of obtaining loans online, often with minimal human interaction, may lead to a less rigorous assessment of a borrower's true ability to repay. As a result, loans may be extended to businesses or individuals who are fundamentally not creditworthy, leading to business closures and employment reductions. Thus, online lending may exacerbate financial distress, ultimately leading to job downsizing.

Given these conflicting arguments, we consider the impact of online lending on employment change without an *a priori* directional prediction. This leads us to present our hypothesis in the null form:

H0: There is no significant relationship between online lending and employment.

3. Data and Methodology

3.1 Data

We obtain data on online lending from Lending Club, which provides loan information at the individual level, including origination date, the amount of loans applied by the borrower, principal amount paid, purpose, term (36- or 60- months), and last payment date. The data are available from 2007 to 2020 (n = 2,925,493 loans).[3] We obtain employment data from Quarterly Workforce Indicators (QWI), which covers the U.S. labor market statistics by county. We also obtain other county information from QWI and the Bureau of Economic Analysis (BEA). After merging QWI data with data on LC lending and other county information using 3-digit zip codes and county FIPS codes, our final sample comprises of 45,756 county-year observations, representing 3,143 unique counties across 52 states.

For each year, loans were coded as either being outstanding or in default. Specifically, mature loans (i.e., those whose terms had expired) marked as paid by LC were coded as outstanding for each year from loan origination to payoff. Immature loans listed as current or late were coded as outstanding for each year from loan origination until 2020, which marked the end of our data collection period. Loans that LC marked as in default or charged off were coded as outstanding for each year from loan origination until the last year payment was received. In the subsequent year, these loans were then coded as in default.

[3] LC no longer publishes loan data from 2021 onwards.

As our analysis is at the county level, we proceed to count the number of loans outstanding in each county *i*. County-level analysis enables us to control for local demographic and economic variables, thereby improving the precision of our estimates of LC's impact on local employment. Consequently, while unobserved state-level factors may influence both LC loans and job change, these effects may not persist at the county level.

3.2 Employment measures

We construct three key variables to measure annual employment dynamics at the county level. The first variable, job loss (*Destruction*) is the natural logarithm of one plus annual sums of quarterly job losses of a county in a year. We use this measure to capture the contraction side of the labor market, indicating the extent to which positions were eliminated or became redundant. The second variable, job gains (*Gain*) is the natural logarithm of one plus annual sums of quarterly job gains of a county in a year. This measure reflects the expansion side of the labor market, quantifying the creation and filling of new positions. The third variable, replacement hires (*Replace*) is the natural logarithm of one plus the difference between annual hires into continuous employment and annual job creation of a county in a given year. This measure captures the annual churn in the labor market beyond net job creation. A significant decrease in replacement hires indicates a stagnant job market, reflecting reduced workforce mobility and diminished dynamism. Overall, *Destruction*, *Gain,* and *Replace* provide a comprehensive view for understanding labor market conditions, encompassing job destruction, job creation, and labor market fluidity.

3.3. Baseline Model

To examine the effect of LC lending on employment change, we estimate the following baseline panel ordinary least squares (OLS) regression model:

$$Employment_{it} = \alpha_0 + \alpha_1 Loans_{it-1} + \gamma X_{i,t-1} + \emptyset_t + \varphi_i + \varepsilon_{i,t} \qquad (1)$$

Where i and t denote county and year respectively. The dependent variable, $Employment$, denotes our three measures of employment. Our variable of interest, $Loans$, is LC loans outstanding per capita in county *i* in year *t*.

The model also includes a set of control variables, X, that have been previously documented to influence employment change (Boustanifar, 2014; Wang and Overby, 2022; Ozer et al., 2023). These variables include the proportion of the county's population that identifies as male (*Male*), the proportion of the county's population that is 55 years old and older (*Age*), the proportion of the county's population that identifies as white (*White*), the proportion of the county's population that has achieved an educational level higher than a high school diploma (*Education*), the total number of residents in the county (*Population*), the average personal income per capita in the county (*Income*), unemployment rate (*Unemploy*). The model specification includes year fixed effects ($\emptyset$) and county fixed effects (φ). In all regressions, we report in parentheses t-statistics based on robust standard errors clustered by county. Descriptive statistics are in Table 1 and Pearson correlations are in Table 2. As reported in Table 2, *Destruction* exhibits a positive correlation with *Loans*, whereas *Gain* and *Replace* show negative correlations with *Loans*. The findings suggest that an increase in LC loans is associated with a decrease in overall employment levels.

4. Empirical Results

4.1 Baseline Results

Table 3 reports the baseline regression results of Equation (1). In column (1), where the dependent variable is *Destruction*, we find that the coefficient is positive and significant at the 1% level, indicating that greater LC loan activities are associated with higher job destruction.

The economic magnitude is also significant. A one-standard-deviation increase in LC loans per capita corresponds to a 2.989% increase in job destruction.[4] Column (2) uses *Gain* as our dependent variable revealing a negative and significant coefficient at the 1% level, suggesting that greater LC loans per capita are associated with lower job creation. Economically, a one-standard-deviation increase in LC loans per capita decreases job creation by 1.802%. In column (3), with *Replace* as the dependent variable, the coefficient remains negative and significant at the 1% level, implying that greater LC loan activities are linked to fewer replacement hires. This effect is also economically significant, with a one-standard-deviation increase in LC loans per capita corresponding to a 2.418% decrease in replacement hires. Collectively, these findings suggest that LC loans have a negative impact on employment across multiple dimensions of labor market dynamics.

4.2. Addressing Endogeneity Issues

Our analysis is potentially subject to endogeneity issues since LC loans are not randomly determined. One potential source of endogeneity is that there are underlying unobservables that simultaneously drive a county's lending activities and employment change. To alleviate these concerns, we conduct two empirical approaches, a quasi-natural experiment and an instrumental variable (IV) approach. The quasi-natural experiment exploits state regulatory granted approval for LC as an exogenous shock to increase LC loans. The IV approach uses the debt-to-income ratio policy, which raises the borrowing threshold for eligible borrowers as an instrument for LC's lending.

4.2.1 Quasi-Natural Experiment: LC availability

[4] Economic significance is based on the coefficient of *Loans* times by the standard deviation of *Loans* and then divided by the mean of relevant dependent variable (i.e., *Destruction, Gain, Replace*)

We follow the prior literature (Wang and Overby, 2022; Ozer et al., 2023) in utilizing LC regulatory approval process as a quasi-natural experiment to establish the causal effect of lending activities on employment. LC launched its platform in 2007. In April 2018, LC entered a quiet period in which it suspended peer-to-peer lending until it could register as a licensed lender with federal and state regulators. During the quiet period, LC funded a limited number of loans with its own money rather than investors' money. Subsequently, LC pursued regulatory approval to resume peer-to-peer lending across all 50 states. By October 2018, the platform had received approval in 40 states and the District of Columbia. Nine additional states granted approval at different times between 2010 and 2016. One state (Iowa) has not received approval as of 2021. Appendix II shows the year in which LC received regulatory approval in each state. The variation in when states allowed LC to resume peer-to-peer lending represents an exogenous increase in loans outstanding per capita for treated counties compared with untreated counties serving as controls.

We then use LC regulatory approval to estimate a difference-in-differences regression as follows:

$$Employment_{i,t} = \alpha_0 + \alpha_1 LCavailable_{i,t} + \gamma X_{i,t} + \emptyset_t + \varphi_i + \varepsilon_{i,t} \qquad (2)$$

Where *i* and *t* refer to the county and year respectively. In Equation (2), the dependent variable *Employment* represents three distinct variables that capture various dimensions of employment. The key variable of interest, *LCavailable* is an indicator variable that equals 1 if LC has been authorized to operate in county *i* in year *t*. *X* consists of county characteristics described in Section 3.3.

The results are reported in Table 4, showing that the coefficient of *LCavaiable* is positive and significant on *Destruction* at the 1% level, whereas the coefficients on *Gain* and

Replace are negative and significant at the 1% level, with a similar economic magnitude as that reported in the baseline results in Table 3. Overall, these results provide significant evidence in support of our baseline findings by demonstrating a likely causal and negative effect of LC loans outstanding on employment.

4.2.2 Instrumental Variable Approach: Debt-to-income policy change in 2012

Following Wang and Overby (2022), we use debt-to-income (DTI) policy change, initiated by LC in 2012, as an instrument for LC loans. This policy prohibits LC from issuing loans if an applicant's DTI ratio exceeds a certain threshold. In 2012, LC raised this threshold from 0.3 to 0.35, which effectively expanded the pool of qualified borrowers, leading to an increase in loan outstanding per capita. As a result, the DTI policy change satisfies the relevance criterion for a valid instrument. Moreover, the policy was implemented uniformly across all counties as a blanket change, rather than being tailored to specific local economic conditions. Therefore, it does not independently account for variations in employment across counties. There is no theory and empirical evidence to suggest that the DTI policy affects directly employment other than through the LC lending market. Thus, we assume that the DTI policy meets the exclusion condition to constitute a valid instrument. We then employ the following two-stage regressions:

First-stage regression:

$$Loans_{i,t} = \alpha_0 + \alpha_1 DTIPolicy_{i,t} + \gamma X_{i,t} + \emptyset_t + \varphi_i + \varepsilon_{i,t} \qquad (3)$$

Second-stage regression:

$$Employment_{i,t} = \alpha_0 + \alpha_1 \widehat{Loans}_{i,t} + \gamma X_{i,t} + \emptyset_t + \varphi_i + \varepsilon_{i,t} \qquad (4)$$

Where i and t refer to the county and year respectively. In Equation (3), *Loans* represent LC loans outstanding per capita. *DTIPolicy* is an indicator variable that equals 1 for all years from 2012 onwards and in counties in which LC has been authorized to borrow. In Equation (4), $Employment$ represents three different measures of employment. $\widehat{Loans}$ is the predicted value of Loans from Equation (3). *X* consists of county characteristics described in Section 3.3.

We report the results in Table 5. The first-stage regression shows that the coefficient of *DTIPolicy* is positive and significant at the 1% level. This evidence supports our argument that the DTI policy change meets the relevance criterion for a valid IV by demonstrating that LC lending constraints tend to face greater loans outstanding per capita. In the second-stage regressions, the coefficient on *Destruction* is positive and significant at the 1% level. Similarly, the coefficients on *Gain* and *Replace* are negative and significant at the 1% level. These results corroborate our baseline findings, showing that the negative effect of loans outstanding on employment remains robust to this instrumental variable regression.

4.3 Underlying Mechanisms

4.3.1 The debt trap mechanism

One could argue that this ease of access may encourage these borrowers to accumulate more debt than they can sustainably manage (Jagtiani and Lemieux, 2017). As debt obligations mount, borrowers—particularly small business owners—face escalating pressure to meet repayment terms. To avoid loan acceleration and maintain access to credit, these borrowers may implement cost-cutting measures such as employee layoffs. This action allows businesses to reduce operating costs and demonstrate to lenders their commitment to loan repayment, albeit at the expense of local employment. Therefore, we expect that the negative effect on employment should be stronger for the counties with higher debt burden borrowers.

To test our hypothesis, we use two proxies for borrower's leverage. The first measure is debt expansion. For each loan application, the borrower selects the purpose of the loan from a pre-defined list. Two choices indicate debt consolidation: credit card and debt consolidation. We follow Wang and Overby (2022) and code debt expansion for loans with a purpose other than these two, such as home improvement, major purchase, and vacation. We count for the purpose of the loan to expand the borrower's overall debt for each county and define debt expansion (*Debt Expansion*) by dividing the number of debt expansions by the total number of borrowers in each county. The second measure is the average debt-to-income (DTI) ratio, weighted by the borrowers' DTI in each county. We then interact *Loans* with either *Debt Expansion* or *DTI* and include both the interaction term and *Debt Expansion* or *DTI* as the additional variables in the baseline regression model. We report the results in Table 6.

The results show that the coefficients for *Loans x Debt Expansion* and *Loans x DTI* on *Destruction* are negative and significant at the 1% level, while the coefficients for *Loans x Debt Expansion* and *Loans x DTI* on *Gain* and *Replace* are positive and significant at least the 5% level. These results imply that the negative effect of LC loans on employment is more pronounced for counties with higher leverage borrowers, supporting the debt trap mechanism.

4.3.2 The credit risk mechanism

Another mechanism to explain the observed relationship between LC loans and employment is by extending credit to inherently uncreditworthy borrowers. LC's algorithmic underwriting may approve loans for individuals or businesses that traditional lenders would typically reject. These high-risk borrowers, upon receiving funds, may invest in unsustainable ventures or use the money inefficiently. Due to their inherent lack of creditworthiness, these borrowers are more likely to experience financial difficulties. Consequently, this leads to business closures or downsizing, resulting in job losses and negative employment in the affected areas. We expect the negative effect on employment should be stronger for unquantified borrowers.

To test this hypothesis, we use two proxies for the borrower's creditworthiness. The first proxy is based on the FICO scores of LC borrowers. A higher value of the FICO score corresponds to a lower credit risk. The mean FICO score is 689, which is similar to the mean FICO scores reported in credit bureau data (Jagtiani and Lemieux; 2019). We construct the weighted average of borrowers' FICO scores for each county and take the logarithm of one plus the average of FICO scores (*Credit Score*). Re-estimating Eq. (1) by interacting *Loans* with *Credit Score,* we find that the coefficient of *Loans x Credit Score* on *Destruction* becomes negative and significant at the 1% level, whereas the coefficients of *Loans x Credit Score* on *Gain* and *Replace* become positive and significant at the 1% level, as reported in the Panel A of Table 7. The results suggest that the constraining effect on employment is weaker for counties with greater credit scores.

The second proxy is based on the business life cycle stages. We define the proportion of businesses age equal and below five years as high-risk businesses (*StartUp*) because start-ups have a high probability of perishing within their first five years due to their limited credit history and higher perceived risk (Murro et al., 2022). Panel B in Table 7 shows the estimation results for Equation (1) interacted with *Loans* and *StartUp*. We find that the coefficient of *Loans x StartUp* on *Destruction* is positive and significant at the 1% level, whereas the coefficients of *Loans x StartUp* on *Gain* and *Replace* are negative and significant at the 1% level. The results suggest that the start-ups experience a more pronounced reduction in jobs.

4.3.3 Default and Bankruptcy

To illuminate the pathways through which LC lending might influence local labor market, we examine the relationship between LC loans and two critical indicators of financial distress: loans defaults and bankruptcy filings. First, when borrowers struggle to meet their loan obligations, they often resort to cost-cutting measures,, with workforce reduction being a common strategy (Bai, 2021). If LC loans indeed lead to job downsizing by creating financial pressures that constrain borrowers' ability to repay, we would expect to observe a positive correlation between increased loan volume and default rates.

To test this hypothesis, we quantify loan defaults by calculating the natural logarithm of one plus the number of defaults in each county (*Default*). We then re-estimate our baseline regression, substituting the employment measure with *Default*. The results of this analysis are presented in Column (1) of Table 8. The coefficient of *Loans* variable is positive and significant at the 1% level, indicating that the increased lending volume from LC is positively associated with loan defaults in the affected counties. These results support our expectation that LC loans impose financial pressures on borrowers' risk of default.

Since bankruptcy is a possible venue through which employment is reduced more often (Bernstein et al., 2019), we next examine the effect of LC loans on bankruptcy filings. Following prior literature (Wang and Overby, 2021), we define bankruptcy as the number of bankruptcies filings per capita in a county year. In column (2) of Table 8, the coefficient of *Loans* is positive and highly significant, suggesting that counties with higher LC loan volumes experience a significant increase in bankruptcy filings.

5. Additional Analysis

5.1 Moderation tests

To further explore and validate our baseline results, we examine the socioeconomic factors on the relationship between online lending and employment across three key dimensions: (1) level of education, (2) internet access, and (3) concentrated banking markets.

5.1.1 Level of education

Prior research (Howard et al., 2001; Bonfadelli, 2002) suggests that individuals with higher educational attainment typically possess the digital literacy and financial acumen to leverage online lending platforms effectively, potentially enhancing their financial and social capital. However, Melzer (2011) suggests that less educated borrowers often struggle to accurately assess the cost-benefit ratio of high-interest borrowing, leading to more frequent borrowing and the accumulation of substantial debt burdens. This can trap them in a cycle of borrowing and interest payments, potentially impacting their long-term financial stability and employment prospects. Given these disparities, we hypothesize that the negative impacts on employment should be less observed in counties with higher education levels.

To test this, we use the proportion with above high school education (*Education*) as a proxy for education county level and interact *Education* with *Loans* and and re-estimate our baseline regression in Equation (1) by including *Education* and its interaction. We present the results in Panel A of Table 9, showing that the coefficient of interaction term on *Destruction* is negative and significant at the 1% level and coefficients on *Gain* and *Replace* are positive and significant at the 1% level. These results suggest that the negative effect of loans outstanding per capita on employment is alleviated for counties with high education levels.

5.1.2 Internet Access

The extent of internet access prevalence varies across different regions. Regions with widespread internet access provide a fertile ground for the proliferation and utilization of online lending platforms such as Lending Club (Hargittai and Hinnant, 2008). In these areas, individuals and businesses have greater exposure to and familiarity with digital financial services, potentially leading to increased adoption of online lending options. Therefore, we expect that the negative effects of online lending on employment should be more pronounced in areas with widespread internet access.

Following prior literature (Wang and Overby, 2022), we use the county's annual internet score as a proxy for the level of Internet access (*Internet Score*) for each county from the Federal Communications Commission's Form 477 County Data. Scores are integers from zero to five and are based on the number of high-speed connections per 1,000 households in the county (e.g., zero represents zero connections, one represents between zero and 200 connections, etc). We interact *Internet Score* with *Loans* for each county year and re-estimate our baseline regressions in Equation (1) by including *Internet* and its interaction.

Panel B of Table 9 shows the coefficient of interaction term on *Destruction* is positive and significant at the 5% level, and the coefficients on *Gain* and *Replace* are negative and significant at the 5% level or better. These results suggest that the negative effect of loans outstanding on employment is more pronounced in counties in which internet access is widespread.

5.1.3 Concentrated banking markets

One could argue that online lending activities penetrate areas that are underserved by traditional banks (Jagtiani and Lemieux, 2018), thus expanding access to capital as an alternative funding source. Research on Fintech (e.g., Gopal and Schnabl, 2022) has found that Fintech lending processes loan applications faster than banks, improving the efficiency of financial intermediation in the mortgage market. We, therefore, expect that the negative association on employment will be stronger in the area where there is less competition in banking services.

To test our hypothesis, we follow prior literature and use a measure of bank market concentration (*Bank HHI*) to capture a county's bank competition. The variable, *Bank HHI*, is defined as the sum of each bank's squared deposits at the county level. A high value of *Bank HHI* indicates weaker competition. Re-estimating Equation (1) by interacting *Loans* with *Bank HHI*, we find that the coefficient of interaction term on *Destruction* is positive and significant at the 1% level, as Panel C of Table 9 shows, and the coefficients on *Gain* and *replace* are negative and significant at the 1% level. These results indicate that the negative effect of loans outstanding on employment is more pronounced in areas with highly concentrated banking markets.

5.2 Robustness Tests

5.2.1 Alternative proxies for employment change

We use *Change* as an alternative measure of employment change. This measure is defined as natural logarithm of one plus the difference between job gain and job loss of a county in a year. In addition, we also proxy for employment change using *Replace Rate,* which is the weighted average of replacement hires as a percent of the average of beginning and end-of-quarter employment. We re-estimate the baseline model and report the result in Panel A of Table 10. We find that coefficients on *Change* and *Replace Rate* remain negative and significant at the 1% level, suggesting that our results are robust to this alternative proxy for employment change.

5.2.2 Controlling for house price change

The demand for online lending might coincide with house price changes at the county level which would affect employment. Adelino et al. (2013) and Schmalz et al. (2013) argue that rising house prices facilitate greater access to collateral for entrepreneurs, potentially stimulating employment growth. To account for this factor, we incorporate house price data (*House Price*) from Zillow Research into our model. The results, presented in Panel B of Table

10, demonstrate that the negative effect of online lending on employment persists even after controlling for housing prices. This finding suggests that the relationship between online lending and employment is robust and unlikely to be driven by housing market dynamics.

5.2.3 Additional tests

We conduct two additional tests to assess the robustness of our findings. First, we exclude the sample after 2016 from the regression analysis. The reason is that after the Federal Reserve's December 2015 rate hike, about three-quarters of applicants sought loans from online platforms primarily to refinance revolving consumer credit card debt (Bertsch et al., 2017). To eliminate the obstacle of the interest rate hike policy, we re-estimate the baseline regression and present the results in Panel C of Table 10. We find that the negative effect of the online lending platform on overall employment still remains. Second, we incorporate Prosper.com available (*Prosper*) as another control to examine the effect on employment of Prosper.com, which is another prominent lending platform similar to Lending Club[5]. We take the value of one from the year Prosper.com has been authorized to operate in county *i*, and zero otherwise. Results are shown in Panel D of Table 10. Aligning with our findings regarding LC, it reveals Prosper.com's presence also exerts a negative impact on employment.

6. Conclusion

This study examines the impacts of online lending on employment levels cross U.S. counties. We employ a new measure of county-level online loan penetration by observing the proportion of LC loans outstanding relative to the population in the lending market. Using a sample of U.S. counties during 2007 – 2020, we find that counties with greater proportions of

[5] Online lending in US has historically been dominated by two major platforms – Prosper and Lending Club, whose joint market share was 98% in 2014 and 67% in 2018.

LC loans outstanding tend to experience reduced employment levels. This evidence supports the down-spiral hypothesis, which posits that online lending exacerbates financial distress, thus leading to job losses.

Our findings are robust to a series of analyses designed to mitigate endogeneity concerns, including a difference-in-differences approach using LC regulatory approval as an exogenous shock to LC loans outstanding and an instrumented variable approach utilizing debt-to-income policy change as an instrumental variable for LC loans outstanding. The observed decrease in employment is attributable to borrower's debt traps or diminished creditworthiness. Furthermore, the relationship between online lending and reduced employment remains strong even when accounting for changes in house price.

This study provides the first empirical evidence linking online lending to employment outcomes, revealing a potential drawback of online lending platforms. Our findings have important implications of platform design and regulation for LC. However, we acknowledge that our findings are limited to connect individual LC borrowers to special employment records. Future research could explore how individual borrowers of online lending platforms affect personal financial well-being and employment status.

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Appendix I Variable Definition

Variables	Definition	Source
Destruction	The natural logarithm of one plus the number of jobs lost of a county in a year	Quarterly Workforce Indicators
Gain	The natural logarithm of one plus the number of jobs gained of a county in a year	Quarterly Workforce Indicators
Replace	The natural logarithm of one plus the number of hires that are replacing others who are leaving of a county in a year	Quarterly Workforce Indicators
Loan	Ratio of total Lending Club loans outstanding to total population in a county	Lending Club
Male	Percentage of Male	Quarterly Workforce Indicators
Age	Percentage of age equal and above 55	Quarterly Workforce Indicators
Education	Percentage of high school or higher	Quarterly Workforce Indicators
White	Percentage of white residents	Quarterly Workforce Indicators
Population	The natural logarithm of one plus the number of residents	Quarterly Workforce Indicators
Income	Ratio of personal income to population	Bureau of Economic Analysis
Unemploy	Rate of unemployment	Bureau of Economic Analysis
Bank HHI	HHI calculated with each bank's market share in the county	Federal Deposit Insurance Corporation
Default	Natural logarithm of one plus the number of defaults	Lending Club
Debt Expansion	Natural logarithm of one plus the number of the loans purpose was to expand debt	Lending Club
DTI	The weighted average of the borrower's debt to income ratio	Lending Club
Credit Score	The weighted average of the borrowers' FICO scores	Lending Club
StartUp	Percentage of firms age equal or below 5 years	Quarterly Workforce Indicators
Internet Score	Internet access score of a county in a year. Scores are integers from zero five and are based on the number of high-speed connections per 1000 housing units. Zero represents zero connections, one represents between zero and 200 connections, two represents between 200 and 400 connections, three represents 400 and 600 connections, four represents between 600 and 800 connections, and five represents more than 800 connections	Federal Communications Commission
Change	The natural logarithm of one plus the difference between job gains and job lost of a county in a year	Quarterly Workforce Indicators
Replace Rate	The weighted average of replacement hires as a percent of the average of beginning and end of quarter employment	Quarterly Workforce Indicators
House Price	The natural logarithm of house value	Zillow Research
LCavailable	An indicator variable that equals 1 if Lending Club received regulatory approval in a county in a year	Lending Club
Prosper	An indicator variable that equals 1 if Prosper received regulatory approval in a county in a year	Prosper

Appendix II Lending Club Approval by State

State	Approval Year
All state, except those listed below	2008
Kansas (105 counties)	2011
North Carolina (100 counties)	2011
Indiana (92 counties)	2013
Tennessee (95 counties)	2013
Mississippi (82 counties)	2014
Nebraska (93 counties)	2015
North Dakota (53 counties)	2015
Maine (16 counties)	2015
Idaho (44 counties)	2016
Iowa (99 counties)	Not approval as of 2021

This table shows the year in which Lending Club received regulatory approval in each state.

Table 1 Summary Statistics

	N	Mean	SD	Min	p25	Median	p75	Max
Destruction	45756	6.559	1.649	.084	5.592	6.694	7.7	12.907
Gain	45756	7.316	1.650	0	6.17	7.18	8.302	13.696
Replace	45756	7.606	1.802	0	6.392	7.516	8.7	14.08
Loan	45756	1.735	5.565	0	0	0	4.003	26.946
Male	45756	.549	0.058	.148	.515	.542	.578	1
Age	45756	.141	0.032	0	.119	.136	.158	.545
Education	45756	.564	0.045	.25	.538	.564	.59	1
White	45756	.787	0.129	.067	.713	.82	.884	1
Population	45756	10.265	1.482	4.06	9.299	10.155	11.115	16.13
Income	45756	10.554	0.270	9.524	10.37	10.534	10.714	12.801
Unemploy	45756	6.269	2.908	.8	4.1	5.6	7.9	29.4

This table presents the summary statistics for the sample. Definitions of the variables are provided in Appendix I.

Table 2 Pearson Correlation Results

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Destruction	1.000										
(2) Gain	-0.996	1.000									
(3) Replace	-0.984	0.978	1.000								
(4) Loans	0.258	-0.260	-0.251	1.000							
(5) Male	-0.153	0.164	0.166	-0.071	1.000						
(6) Age	-0.256	0.272	0.257	-0.043	-0.003	1.000					
(7) Education	-0.145	0.148	0.151	-0.066	0.066	0.325	1.000				
(8) White	-0.282	0.284	0.280	-0.119	0.112	0.141	0.151	1.000			
(9) Population	0.956	-0.963	-0.955	0.250	-0.206	-0.305	-0.178	-0.337	1.000		
(10) Income	0.276	-0.270	-0.260	0.118	0.023	0.276	0.054	0.030	0.150	1.000	
(11) Unemploy	0.032	-0.026	-0.054	-0.103	0.014	-0.128	0.100	-0.142	0.105	-0.464	1.000

This table presents the correlation matrix. Definitions of the variables are provided in Appendix I. ***, ** and * respectively indicate the 1%, 5%, and 10% significance levels

Table 3 Lending Club loans and employment

	(1)	(2)	(3)
	Destruction	Gain	Replace
Loans	0.113***	-0.076**	-0.106***
	(3.289)	(-2.194)	(-3.309)
Male	-0.523***	0.814***	0.319***
	(-9.032)	(12.173)	(4.335)
Age	0.703***	-0.766***	-0.626***
	(5.613)	(-5.886)	(-4.381)
Education	-0.959***	1.059***	-0.377***
	(-11.397)	(11.995)	(-3.856)
White	0.558***	-0.437***	-1.423***
	(6.656)	(-4.995)	(-15.154)
Population	-1.097***	1.117***	1.100***
	(-31.129)	(28.216)	(28.136)
Income	-0.469***	0.423***	0.512***
	(-12.394)	(12.387)	(13.793)
Unemploy	0.020***	-0.018***	-0.044***
	(17.110)	(-14.034)	(-32.274)
N	45756	45756	45756
R2	0.990	0.989	0.993
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes

This table presents the results examining the relationship between Lending Club loans outstanding and employment. All variables are defined in Appendix I. Standard errors are clustered by county, and t-statistics are reported in parentheses below the coefficients. ***, ** and * respectively indicate the 1%, 5%, and 10% significance levels.

Table 4 Endogeneity – Lending Club regulatory approval by state

	(2) Destruction	(3) Gain	(4) Replace
LCavailable	0.044***	-0.042***	-0.034***
	(7.354)	(-6.743)	(-5.299)
Male	-0.525***	0.816***	0.320***
	(-9.105)	(12.230)	(4.367)
Age	0.706***	-0.769***	-0.629***
	(5.637)	(-5.912)	(-4.404)
Education	-0.949***	1.049***	-0.384***
	(-11.299)	(11.892)	(-3.933)
White	0.552***	-0.432***	-1.418***
	(6.613)	(-4.952)	(-15.168)
Population	-1.093***	1.114***	1.096***
	(-31.075)	(28.306)	(27.978)
Income	-0.463***	0.417***	0.508***
	(-12.310)	(12.279)	(13.733)
Unemploy	0.020***	-0.018***	-0.044***
	(17.105)	(-14.042)	(-32.265)
N	45756	45756	45756
R2	0.990	0.989	0.993
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes

This table presents the difference-in-differences analysis regression results when Lending Club regulatory approval is used as the exogenous shock for Lending Club loans outstanding. All variables are defined in Appendix I. Standard errors are clustered by county, and t-statistics are reported in parentheses below the coefficients. ***, ** and * respectively indicate the 1%, 5%, and 10% significance levels.

Table 5 Endogeneity – Debt-to-income policy change in 2012

	(1)	(2)	(3)	(4)
	Loans	Destruction	Gain	Replace
	First stage	Second Stage	Second Stage	Second Stage
DTI policy	0.012***			
	(14.350)			
Loans		0.278***	-0.271***	-0.241***
		(5.018)	(-4.838)	(-4.156)
Male	-0.000	-0.052***	0.082***	0.032***
	(-0.184)	(-8.946)	(12.133)	(4.329)
Age	-0.002	0.071***	-0.077***	-0.063***
	(-0.416)	(5.606)	(-5.869)	(-4.396)
Education	-0.021***	-0.091***	0.101***	-0.042***
	(-6.248)	(-10.713)	(11.403)	(-4.295)
White	-0.021***	0.061***	-0.049***	-0.147***
	(-5.409)	(7.203)	(-5.540)	(-15.424)
Population	0.041***	-0.121***	0.123***	0.120***
	(9.480)	(-26.009)	(25.005)	(23.583)
Income	-0.019***	-0.041***	0.037***	0.046***
	(-9.280)	(-10.160)	(9.864)	(12.066)
Unemploy	-0.000	0.002***	-0.002***	-0.004***
	(-0.157)	(16.477)	(-13.695)	(-31.657)
N	45756	45756	45756	45756
R2	0.817	0.033	0.043	0.185
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes

This table presents the instrumental regression results when Debt-to-income policy is issued as the instrument for Lending Club loans outstanding. All variables are defined in Appendix I. Standard errors are clustered by county, and t-statistics are reported in parentheses below the coefficients. ***, ** and * respectively indicate the 1%, 5%, and 10% significance levels.

Table 6 The moderating effect of debt traps

	(1)	(2)	(3)
	Destruction	Gain	Replace
Panel A Debt Expansions			
Loans x Debt Expansion	0.676***	-0.606***	-0.458**
	(3.197)	(-2.706)	(-2.298)
Loans	0.195***	-0.266***	-0.081
	(3.236)	(-4.109)	(-1.505)
Debt Expansion	0.082**	-0.068	-0.074**
	(2.099)	(-1.640)	(-1.988)
N	45756	45756	45756
R2	0.990	0.986	0.993
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Panel B Borrowers' Leverage Ratios			
Loans x DTI	0.146***	-0.170***	-0.145***
	(3.524)	(-3.845)	(-3.406)
Loans	0.286***	-0.363***	-0.135**
	(4.136)	(-5.119)	(-2.114)
DTI	0.012***	-0.009**	-0.016***
	(2.728)	(-2.009)	(-3.691)
N	45756	45756	45756
R2	0.990	0.986	0.990
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes

This table presents the regression results of the impact Lending Club loans outstanding have on employment when moderated by debt expansions and the borrowers' leverage ratios. All variables are defined in Appendix I. Standard errors are clustered by county, and t-statistics are reported in parentheses below the coefficients. ***, ** and * respectively indicate the 1%, 5%, and 10% significance levels.

Table 7 The moderating effect of creditworthiness

	(1) Destruction	(2) Gain	(3) Replace
Panel A Credit rating, FICO			
Loans x Credit Ratings	-0.173**	0.254***	0.264***
	(-1.964)	(2.992)	(3.246)
Loans	0.204***	-0.250***	-0.275***
	(3.612)	(-4.597)	(-5.241)
Credit Ratings	-0.018***	0.017***	0.019***
	(-8.229)	(8.051)	(8.189)
N	45756	45756	45756
R2	0.987	0.988	0.990
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Panel B Proportion of High-Risk Businesses			
Loans x StartUp	0.362***	-0.272***	-0.176***
	(6.813)	(-4.963)	(-4.266)
Loans	0.119***	-0.084***	-0.051***
	(6.285)	(-4.230)	(-3.454)
StartUp	-0.003	0.000	0.001
	(-0.899)	(0.128)	(1.174)
N	45756	45756	45756
R2	0.990	0.986	0.993
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes

This table presents the regression results of the impact Lending Club loans outstanding have on employment when moderated by the borrowers' creditworthiness and proportion of high-risk businesses. All variables are defined in Appendix I. Standard errors are clustered by county, and t-statistics are reported in parentheses below the coefficients. ***, ** and * respectively indicate the 1%, 5%, and 10% significance levels.

Table 8 Dependent variable: number of defaults and bankruptcy filings

	(1) Default	(2) Bankruptcy Filings
Loans	0.066***	0.042***
	(14.320)	(4.879)
Male	-0.001***	0.001*
	(-2.676)	(1.650)
Age	0.001	-0.007***
	(1.319)	(-2.904)
Education	0.003**	-0.004**
	(2.420)	(-1.981)
White	-0.004***	0.009***
	(-2.799)	(5.108)
Population	0.024***	-0.029***
	(9.537)	(-8.533)
Income	0.005***	-0.010***
	(5.129)	(-5.388)
Unemploy	-0.000***	0.000***
	(-2.877)	(3.578)
N	45756	42500
R2	0.452	0.805
Year FE	Yes	Yes
County FE	Yes	Yes

This table presents the regression results examining the relationship between Lending Club loans outstanding and default risk and bankruptcy filings respectively. All variables are defined in Appendix I. Standard errors are clustered by county, and t-statistics are reported in parentheses below the coefficients. ***, ** and * respectively indicate the 1%, 5%, and 10% significance levels.

Table 9 Socioeconomic Factors

	(1) Destruction	(2) Gain	(3) Replace
Panel A Education			
Loans x High Education	-0.432***	0.323***	0.282***
	(-4.654)	(3.612)	(2.899)
Loans	0.250***	-0.186***	-0.154***
	(4.918)	(-3.800)	(-2.872)
High Education	-0.093***	0.104***	0.088***
	(-10.999)	(11.625)	(8.881)
N	45756	45756	45756
R2	0.990	0.989	0.990
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Panel B Internet Access			
Loans x Internet Score	0.033**	-0.033**	-0.136***
	(2.125)	(-2.125)	(-3.528)
Loans	0.215***	-0.215***	-0.010
	(3.644)	(-3.644)	(-0.620)
Internet Score	-0.039	0.039	-0.003
	(-1.226)	(1.226)	(-0.341)
N	42681	42681	42681
R2	0.989	0.989	0.832
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Panel C Bank Competition			
Loans x Bank HHI	0.221***	-0.202***	-0.377***
	(6.512)	(-5.278)	(-9.015)
Loans	0.058***	-0.069***	-0.014
	(4.468)	(-4.727)	(-0.876)
Bank HHI	0.002	-0.000	-0.004
	(0.736)	(-0.150)	(-1.641)
N	44815	44815	44815
R2	0.954	0.944	0.954
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes

This table reports the effect of Lending Club loans outstanding when local socioeconomical conditions are involved. Panel A shows the effect on counties with higher educational levels. Panel B shows the effect on counties with more widespread internet access. Panel C shows the effect on counties with more banking services. All variables are defined in Appendix I. Standard errors are clustered by county, and t-statistics are reported in parentheses below the coefficients. ***, ** and * respectively indicate the 1%, 5%, and 10% significance levels.

Table 10

Panel A Alternative proxy

	(1)	(2)
	Change	Replace Rate
Loans	-0.100***	-0.004**
	(-5.745)	(-2.471)
N	45756	45756
R2	0.114	0.813
Controls	Yes	Yes
Year FE	Yes	Yes
County FE	Yes	Yes

	(1)	(2)	(3)
	Destruction	Gain	Replace
Panel B Control for house price			
Loans	0.138***	-0.119***	-0.131***
	(4.385)	(-3.655)	(-4.258)
House Price	-0.035**	0.020	0.030*
	(-2.027)	(1.050)	(1.715)
N	35867	35867	35867
r2	0.992	0.991	0.995
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Panel C Restrict the sample before 2016			
Loans	0.248***	-0.186***	-0.101***
	(6.276)	(-4.498)	(-3.014)
N	18066	18066	18066
r2	0.992	0.991	0.995
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Panel D The effect of Similar online lending – Prosper.com			
Loans	0.101***	-0.063*	-0.093***
	(2.946)	(-1.830)	(-2.916)
Prosper	0.046***	-0.050***	-0.049***
	(3.912)	(-4.320)	(-3.167)
N	45756	45756	45756
R2	0.990	0.989	0.993
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes

This table reports additional robustness tests based on the baseline regression model. Panel A reports the regressions using alternative measures of employment. Panel B reports the regressions with changes in house price as an additional control. Panel C restricts the sample before 2016. Panel D reports the regressions where similar online lending platform – Prosper.com is taken into considerations. All variables are defined in Appendix

I. Standard errors are clustered by county, and t-statistics are reported in parentheses below the coefficients. ***, ** and * respectively indicate the 1%, 5%, and 10% significance levels.