Impacts of the Sharing Economy Entry and Regulations on Financial Delinquencies

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Abstract

As home-sharing platforms have continued to grow exponentially in the past decade, regulators are facing policy concerns as they address the impacts of these home-sharing platforms. It is essential for policy makers to understand the economic and societal impacts that these platforms pose as well as the effects of regulatory responses that have developed to date. To answer these questions, this study empirically investigates how Airbnb's entry generates financial liquidity and mitigates financial delinquencies for households affected. On one hand, we show that Airbnb's entry, as a positive shock to household liquidity, reduces mortgage loan and auto loan delinquencies by 3.99% and 2.68%, respectively. On the other hand, the local regulations of home-sharing economy platforms can offset the delinquency dampening effects brought by Airbnb, especially the most restrictive regulations focusing on restricting hosts' access to the platform in certain regions. Further, by supplementing a Panel Vector Autoregression (PVAR) Model with impulse-response analysis, we demonstrate that households prioritize repayment to mortgage loans first, and then auto loans as well as bankcard loans. This paper is consistent with other studies supporting the welfare brought by the sharing economy and has policy implications especially given the excessive household debts and the heated debates on how to regulate home-sharing platforms in the U.S.

Keywords: Sharing Economy, Financial Delinquency; Platform Regulation; Difference-in-Differences

1. Introduction

With the advent of the sharing economy, various sharing economy platforms have experienced exponential growth, and disrupted numerous industries, such as the hotel and transportation industries. Amongst them, home-sharing platforms like Airbnb successfully connect homeowners with spare bedrooms, apartments or entire houses to short-term guests. The benefits of home-sharing platforms are multifold. Underutilized assets are put to use with a much lower "bring-to-market" cost (Filippas et al., 2020), which in turn brings extra earnings to hosts. Besides the lower entry barriers which give hosts more flexibility, consumers also gain access to a wide variety of rental homes for a lower cost. At the same time, the uptake in peer-to-peer rental activities has led to criticism from the public, as well as regulatory and political battles. Critics argue that home-sharing platforms such as Airbnb may lead to a rise in local rents and housing prices due to the crowding out of long-term rentals (Barron et al., 2021), bring negative externality such as noise to neighbors (Filippas and Horton, 2020), and face challenges in curbing racial discrimination on the platform (Edelman et al., 2017; Cui et al., 2019).

Empirical studies show that the economic and societal impacts from home-sharing platforms are non-trivial; however, the concerns and debates about the effects of regulations on home-sharing platforms have never settled. The objectives of regulations on short-term rentals range from reducing pressure for tourism industry, protecting affordable housing, to preserving residential living (Nieuwland and van Melik, 2020). Appropriate regulations protect consumers from safety issues and low-quality service providers, ensure the compliance of taxation, and even encourage entry of incumbents. However, studies raise the concern about the feasibility of regulating such platforms as they offer services via electronic interfaces without physical facilities (Edelman and Geradin, 2016). Moreover, it is difficult for policymakers to propose one regulation that can cater to various communities and types of properties, and effectively fulfill these regulation objectives. On top of that, those regulations may also act as costs to the society because they might offset the dampening effect on financial delinquencies brought by these sharing economy platforms (Nian et al. 2020). For example, McGinnis (2018) argues that the regulations on Airbnb and Uber hamper these companies' contributions to reducing inequality. Home-sharing platforms such as Airbnb help alleviate income inequality because it allows people with low income to monetize their spare housing asset. Therefore, regulations imposed on these platforms may in turn reduce such welfare gains.

Given the intense debates on regulating home-sharing platforms, it is of increasing importance to understand the economic effects brought by home-sharing platforms as well as effects of existing regulation policies. In this study, our first major question is what economic effects home-sharing platforms such as Airbnb have brought to our society. As household debt issues become more severe in the United States,[1] we decide to examine the effect of Airbnb's entry on households' financial delinquencies. We hypothesize that home-sharing platforms allow financially distressed households to capitalize their underutilized housing to obtain supplementary income, which may in turn help reduce households' financial default rates. Therefore, we attempt to answer the following questions: (1) Does Airbnb's entry alleviate financial delinquencies of U.S. households by allowing households to capitalize excess housing capacity? (2) Does the liquidity generated by Airbnb's entry reduce different types of household financial delinquencies such as mortgage, auto and bankcard loans at the same or varying rates?

Our second major question is what economic effects existing regulations imposed on home-sharing platforms have brought to our society. We classify the regulation policies into 3 types: (1) Basic Regulation: include License registration, Tax and Basic Apartment Restrictions; (2) Time-Limit Regulation: include time-span regulations on listing periods or listing periods without hosts; (3) Geo-Location and Prohibitive Regulations: include Prohibited Building List or Prohibited Zoning Areas, the number of short-term rental properties in addition to primary residential ones. Because most existing regulations focus on either restricting homeowners' access to the platform in certain areas or increase costs/barriers for hosts to participate on the platform, those regulations may offset the delinquency dampening effect brought by home-sharing platforms.

To address these questions, we use a comprehensive dataset on households' financial delinquencies at the zip-code level, provided by a major credit bureau in U.S. We investigate the

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[1] U.S. households generally owe debts and retain low-liquidity assets. According to the 2018 American Household Credit Card Debt Study, the amount of credit card loans owned by an average U.S. household is about $6,741, compared to $27,630 for auto loans and $185,591 for mortgages owned by an average U.S. household. By including all types of debt, the survey showed that the amount increases to $135,065 for an average U.S. household. If faced with an unexpected expense of $400, four in ten adults would not be able to cover it or would have to cover it by selling something or borrowing money. One-fifth of adults cannot fully pay their current monthly bill if they had to pay an unexpected expense of $400, including 17% of those would defer at least one bill on rent or mortgage, 49% of them would defer at least one bill on credit card, and 14% of respondents would defer at least one bill on car payment.

impacts of Airbnb's entry on financial delinquencies including mortgages, auto loans and bankcard loans, with a Difference-in-Differences model in conjunction with matching methods. Our research provides supporting evidence that Airbnb's entry significantly reduces financial delinquencies on mortgage and auto loans, but not bankcard loans. We further examine regulations on home-sharing platforms and categorize them based on licensing, time constraint, and zoning prohibition. By comparing regulated areas with comparable unregulated regions, we find that regulations alleviate Airbnb's dampening effects on financial delinquencies. For those states with lower bankruptcy homestead exemption values, Airbnb's entry exerts a stronger effect on reducing mortgage-loan and auto-loan delinquencies. In addition, we discuss households' default and repayment decisions by estimating a Panel Vector Autoregressive Model. Our estimated dynamic effects also imply that households repay multiple loans in a given order, and that in face of liquidity constraint, there may exist an intertemporal choice between repaying auto loans and repaying bankcard loans.

The results of our paper contribute to the extant debates surrounding home-sharing, its impact on household finance and regulations imposed on this industry. To the best of our knowledge, our study is among the first studies investigating the impacts of the entry of sharing economy platforms on zip-code level households' financial decisions. We provide evidence that the burden of repaying mortgage loans can be alleviated by participating in home-sharing platforms, which helps relax liquidity constraints of hosts and improve overall financial well-being.

Our study highlights that regulations of home-sharing platforms bring a potential social cost, as these regulation policies weaken the financial delinquency dampening effects brought by Airbnb's entry. Our view is that regulations on home-sharing platforms should seek to implement policies towards issues such as safety, negative externalities to the communities (e.g. noise, traffic) without discouraging the use of home-sharing by homeowners. Progress in advancing the policy debate surrounding home-sharing platforms requires a better understanding of how households' financial decisions are affected by the extra income generated from Airbnb, as well as the effects of various types of regulation policies. Our study contributes to painting a holistic picture of households' financial decisions when afforded with extra income generated from home-sharing platforms and the social costs of current regulation policies on home-sharing platforms.

2. Literature Review

2.1 Impacts of Sharing Economy Platforms

Extant research has studied the economic impacts of the sharing economy platforms, including Uber, Airbnb among others, on various industries. One of the most direct effects is on the housing market. Barron et al. (2021) studies the impact of Airbnb on the housing market and concludes that it is associated with higher housing costs for city residents and the loss of tax revenue. On the benefit side, digital platforms, such as Airbnb, reduce search frictions and facilitate matching between prospective guests and hosts. Property owners can therefore diversify their streams of revenue by making earnings from short-term rentals, in addition to long-term rentals. Furthermore, home-sharing platforms also enable homeowners to generate incomes from spare housing capacity. Similar results have been documented in Boston that one standard deviation increase in Airbnb listings is associated with an increase in asking rents by 0.4% (Horn and Merante, 2017). However, that study does not distinguish whether the effects arise mainly from the demand side or supply side of the housing market.

In addition to the effects on the housing market, home-sharing platforms have been observed with direct impacts on the competition of the hotel industry, and employment in the tourism industry. Interestingly, the study from Yang et al. (2019) do not find supportive evidence on cost or consumer satisfaction advantages of home-sharing platforms, compared to the hotel industry, but confirms the negative effects of crime rates on consumer demand for home-sharing rentals in destination cities. Regarding the impact of home-sharing platforms on the traditional hotel industry, Zervas et al. (2017) estimate the impact of Airbnb on the hotel industry in Texas: the entry of the platform has a causal negative impact of 8% to 10% on hotel revenue in Austin, and those low-priced hotels are most affected. However, evidence from Dogru et al. (2020) highlights the positive economic spillovers from Airbnb to employment in hospitality and tourism industries. Despite the competition pressure exerted on the traditional hotel industry, home-sharing platforms also expand the demand across multiple related markets. Regulators must balance these competing considerations in determining how to regulate economic activity on home-sharing platforms. A welfare analysis of home-sharing platforms on the accommodation market estimates that in the top 10 U.S. cities, the total welfare would decrease by $137 million and consumer surplus would decrease by $276 million if Airbnb did not exist in 2014. The total welfare would be lower, and travelers and hosts are worse off, while hotels would have faced less competition in the absence of Airbnb (Farronato and Fradkin, 2018).

In addition to these direct impacts on the hotel industry, the housing market and the tourism market, studies also found that home-sharing platforms have brought negative externalities such as noises, crime and congestion, calling for appropriate regulations. Bibler et al. (2018) study the change from partial to full compliance of Airbnb's tax enforcement, and find that at most 24% of Airbnb transactions pay the taxes prior to enforcement. The enforcement of 10% tax reduces hosts' rental income by 2.4%, increases the price paid by renters by 7.6%, and at the same time reduces nights booked by 3.6%. Home-sharing platforms also play a role in boosting demand and gentrification in local communities (Ardura Urquiaga et al., 2020).

Another stream of literature finds significant economic and societal impacts brought by other sharing economy platforms, such as Uber. The entry of Uber has led to reduction in alcohol related motor vehicle fatalities (Greenwood and Wattal, 2017), increases in consumption on durable goods (Gong et al., 2017), decreases in microentrepreneurial activities (Burtch et al., 2018). Regarding the impacts of ride-hailing on public transit and travel patterns, extant literature examines the substitution and supplementary effects on public transportation (Lee et al., 2019; Hall et al., 2018; Babar and Burtch, 2020), and traffic congestion (Agarwal et al. 2019). Moreover, the demand of home-sharing services also interacts with demand of ride-hailing services, leading to an amplification of cross-platform externalities (Zhang et al., 2020).

2.2 Households' Default Decisions

Various studies have explored the economic and societal impacts of the sharing economy; however, its impacts on the households' financial decisions remain unclear: through which channel such an income shock generated by Airbnb's entry affects individuals' decisions on financial defaults. Gelman et al. (2018) demonstrate that people delay payment to mortgage and credit cards to ensure basic consumption and keep low-liquidity assets when facing temporal liquidity shocks. Baker (2018) utilizes shocks from employers and drivers of balance sheet positions, to study the relationship between credit, household balance sheets, income and spending. Given that U.S. households generally retain low-liquidity assets and are financially fragile to unexpected expenses which may trigger financial delinquency, we are interested in the effects of income shocks on consumers' financial delinquencies. A recent study by Cookson et al. (2019) examines the long-run effect of unanticipated wealth shocks on the distribution of household debts. They find heterogeneity among households that subprime households use the additional wealth to pay down debt whereas initially prime households increase debt levels in mortgages and auto loans. Such results also hold for households' financial risk: the wealth shock causes a slight decline in delinquent accounts, whereas the near prime households have a higher likelihood to have delinquent accounts. A research by JP Morgan Institute finds that the relationship between mortgage default and negative income shocks holds for homeowners across all levels of home equity and regardless of income level or total debt-to-income ratio at origination (Farrell et al. 2018). The homeowners promptly resume their mortgage payment after their income recovers. Therefore, based on the literature on how income shocks relax liquidity constraints and improve financial well-being, we argue that individuals prioritize payments to credit card debts, auto loans and mortgage loans over increasing their consumption immediately, when provided with extra income from home-sharing platforms.

Our research joins the literature that examines the impacts of the sharing economy platform on households' financial decisions (Nian et al., 2020; Burtch and Chan, 2018). Our study supplements this stream of literature with evidence on different types of financial delinquencies. Both defaults on mortgage loans and bankruptcies are closely related but are usually supplementary tools for financially distressed homeowners (Li and White, 2009). For example, Mitman (2016) finds that the Bankruptcy Abuse Protection and Consumer Protection Act of 2005 significantly reduces the prevalence of bankruptcies but contributes to the significant rise in foreclosures in the Great Recession. Households choose to file for Chapter 13 bankruptcy when they have low income and significant nonexempt home equity. Households with less nonexempt equity or only exempt equity, file for Chapter 7 bankruptcy, with expectation that most of the debt will be written off. When households have significant negative equity and low income, they default on mortgages and also file for Chapter 7 bankruptcy. As the income of households increases, they are willing to tolerate more negative equity before defaulting but they will only file for bankruptcy if they receive a deficiency judgement.[2] Regarding the driving factors on defaults, Ganong and Noel (2020) study

[2] Deficiency judgement is a ruling made by a court against a debtor in default on a secured loan, that the sale of a property to pay back the loan did not cover the outstanding debt in full. It is a lien placed on the debtor for further money.

whether defaults are primarily driven by a lack of cash to make payments in the short-term or a response to the total burden of long-term debt obligations, known as “strategic default”. They find supportive evidence that households’ default decisions are responsive to immediate payment reductions but not long-term principal reduction, in support of the liquidity-driven theory of default. Dobbie and Song (2020) study the drivers of financial distress by separating the effects of short-run liquidity constraints via immediate minimum payment reductions, and long-run debt overhang via delayed debt write-down. Their results are in contrast to the short-run liquidity constraints but provide supportive evidence for positive outcomes in repayment, bankruptcy and employment from debt write-downs, even though the effects only manifest after 3 to 5 years. Mentioned in Dobbie et al. (2020), bankruptcy is a costly alternative to debt forgiveness as it decreases the borrowers’ access to new credit and new employment opportunities.

3. Hypothesis Development

3.2 Impacts of Home-Sharing Platforms on Household Financial Defaults

Home-sharing platforms may help alleviate income and liquidity constraints. A prevailing theory, “double trigger hypothesis” in mortgage default, suggests that in addition to negative equity, a second shock to the household’s income or liquidity is necessary to trigger default. Cunningham et al. (2020) leverage a natural experiment of a shock -- the fracking boom, and find that mortgage default rates decrease in Pennsylvania due to increased income and employment which further reduce the likelihood of the liquidity-based trigger. Gerardi et al. (2018) find that the job loss alone increases the likelihood of default between 5% to 13%, and the joint occurrence of both job loss and negative equity raises the default rate by 11.3%. The individual employment is considered as the strongest predictor for default, with supportive evidence also from Tian et al. (2016).

We anticipate that in face of multiple loans, the liquidity brought by Airbnb’s entry would not evenly and simultaneously reduce different types of financial delinquencies. For instance, households may choose to repay mortgages, followed by auto loans and bankcard loans, based on monthly payments and interest rates.[3] It is more likely that the income shock from Airbnb, would

[3] Compared to mortgage loans and auto loans, the interest for delaying the payment of credit card loans would be costly, which is charged an average annual percentage rate of 16.46% according to the Federal Reserve Bank of St. Louis. The estimated monthly mortgage payments, based on the 2017 National Profiles of Home Buyers and Sellers,

probably reduce mortgage delinquency first, and then affect auto loans. In order to rent out their homes on Airbnb, hosts would prioritize repaying mortgages to keep their properties. Therefore, the extra liquidity from Airbnb is most likely to reduce the mortgage delinquency. In face of lack of liquidity, people will still keep their homes, because the consequences of defaulting on mortgages are more severe. For instance, defaulting on mortgage loans may prevent borrowers from access to new credits or new employment opportunities (Debbie et al., 2020). The other reason is that liquidity may be more important in the mortgage market, where borrowers usually have fewer outside options compared to credit card borrowers (Debbie and Song, 2020). In addition, as Barron et al. (2021) find that housing prices increase after Airbnb's entry, it is less likely for households to default on mortgage loans due to both the positive liquidity shock and increased net equity in the housing assets, which mitigates the "double trigger" concern on mortgage default. Therefore, we have our first hypothesis as below:

H1: The entry of Airbnb reduces financial delinquencies of mortgage loans.

The determinants for auto loan default are less studied in the literature. Heitfield and Sabarwal (2004) conclude that the default rate for automobile loans is much more sensitive to aggregate shocks, such as unemployment rates. This study suggests that the defaults on subprime auto loans are particularly sensitive to a shock to household liquidity. Agarwal et al. (2008) provide evidence that a rise in unemployment increases the likelihood of default, and they find no significant evidence from increasing income on reducing default. Other factors include the collateral value and tax rates (Ratnadiwakara, 2021). The entry of Airbnb generates a significant income shock to Airbnb hosts and relaxes their liquidity constraints. Thus, we hypothesize that:

H2: The entry of Airbnb reduces financial delinquencies of auto loans.

With respect to bankcard loans, it is found that the short-term liquidity constraints relief cannot reduce the financial delinquencies of bankcard loans (Dobbie and Song, 2020). This observation is consistent with the "credit card debt puzzle" that rational borrowers would hold both significant revolving high-interest credit card debt and low-return liquid assets which could have been used

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are $1,022 per month on a 30-year fixed-rate loan at 4.10%, and $1,505 per month on a 15-year fixed rate loan at 3.43%. In 2015, 85.9% of new cars and more than 50% of used cars were financed through a loan, and the average monthly payment for an auto loan in 2017 were $479, with an average length of 68 months and about 4% of annual interest rate.

to pay down the debt. Telyukova (2013) explains the puzzle that households anticipate the need for liquidity in situations where credit cards cannot be used. Other explanations include the commitment of liquid assets on future expenses (Gross and Souleles, 2002), and the self-control problem such as hyperbolic discounting (Kuchler, 2015). While we expect mortgage and auto loan defaults will decline due to this liquidity shock, such short-term liquidity constraints relief will have a weaker effect on reducing bankcard loan defaults as households may prioritize the use of liquidity to mortgage loans and auto loans. Therefore, our third hypothesis is stated as following:

H3: The entry of Airbnb has a weaker effect on reducing financial delinquencies of bankcard loans.

3.2 Impacts of Regulations on Home-Sharing Platforms

The impacts of local regulation on home-sharing platforms such as Airbnb have attracted widespread discussions and debates across the nation. Regulators need to carefully balance costs and benefits of regulating home-sharing platforms (Nieuwland and van Melik, 2020). Meanwhile, there are rising discussions on self-regulation on home-sharing platforms to internalize those negative effects on local communities. For instance, platforms, building owners, or organizations such as homeowner associations could take up the responsibility of regulation, other than governments (Cohen and Sundararajan, 2015; Edelman and Geradin, 2016; Filippas and Horton, 2020). However, restrictive rules imposed by local governments would, to some extent, increase the barrier of entry, and therefore distort the exchange benefit brought by these peer-to-peer marketplaces. The costs of such distortion include the reduction in income, which is mainly used to supplement living expenses of homeowners or help them repay mortgage loans.

A study of short-term rental regulations in New Orleans shows that the regulations depressed property values by approximately 30%. Specifically, the ordinances reduced participation in the short-term rental markets but shifted the demand to neighborhoods adjacent to the areas that are the most affected (Valentin, 2021). Similar results are found in Kim et al. (2017) in reducing property values or reducing host income (Coles et al., 2017). Within the platform, the regulations on the number of listings may trigger competition effects with higher supply from individual hosts, whereas the platform performance remains stable in terms of reservations and revenue (Chen et al., 2020). Han and Zhang (2020) find that the implementation of license policy from local governments caused a negative effect on individual suppliers, through a supplier-behavior channel.

None of the aforementioned studies have investigated the economic impacts of government regulations on financial delinquencies, which our study aims to answer. Because regulations either increase the barriers/costs for hosts to list their properties on the platform or completely exclude hosts from certain areas to do so, we anticipate that regulations may dampen the benefits brought by Airbnb's entry.

H4: The impacts of Airbnb's entry on financial delinquencies would be weakened by local regulations on home-sharing platforms.

4. Industry Background, Data and Empirical Strategies

Airbnb is among the most prominent peer-to-peer home-sharing platform. According to statistics provided by Airbnb,[4] Airbnb has entered over 220 countries and more than 100,000 cities by 2021, with more than 5.6 million listings worldwide. Nowadays, this lodging platform connect over 4 millions hosts with 1 billion guest arrivals as of September 2021. According to Airbnb,[5] 56% of Airbnb hosts in San Francisco reported that they used income from the platform to pay their mortgage or rent while 42% of hosts in San Francisco used it for regular living expenses. Similar results in New York City highlight that 62% of Airbnb hosts said Airbnb helped them stay in their homes, with more than 50% of hosts being non-traditional workers such as freelancers, part-time, students, and so on. In addition, the average host earns \$7,530 per year in New York City.[6] A typical U.S. host earns \$9,600 each year, which is equivalent to 18% of the median household income \$52,250.[7]

To estimate the impact of Airbnb's entry on households' financial delinquencies, we ideally need to compare the entry of Airbnb to a counterfactual, viz. the potential outcomes of the focal region if Airbnb did not enter. In practice, what we are able to do is to exploit tempo-spatial variation to compare regions that Airbnb entered and regions that Airbnb did not enter. We use a Difference-in-Differences (DID) design to estimate the impact of Airbnb's entry on financial delinquencies. We conduct extensive robustness checks to further validate the robustness of our empirical results.

[4] https://news.airbnb.com/about-us/
[5] https://blog.atairbnb.com/economic-impact-airbnb/
[6] https://blog.atairbnb.com/economic-impact-airbnb/
[7] https://www2.census.gov/library/publications/2014/acs/acsbr13-02.pdf

We proxy the entry of Airbnb at the zip-code level using the date of the first comment left on Airbnb platform, and control for regional socioeconomic conditions using variables from American Community Survey (ACS) including educational attainment, the number of households, median income, poverty rate as well as the unemployment rate. Our financial delinquency dataset covers major metropolitan areas as well as small communities all around the United States, from January 2010 to June 2019. In order to separate the effects of Airbnb's entry from those of regulations, we use the data sample from January 2010 to December 2016 in our first analysis and the data sample from January 2014 to June 2019 in our second analysis, because most regulations have been introduced since 2016. The financial delinquency behavior or decisions of interest includes the monthly number of auto loans, bankcard loans and mortgage loans that are 90 days delinquent at each zip code. We also construct another variable, the general delinquency record (No. of Delinquencies), to denote the filings records that a consumer is 90 days delinquent on any bankcard loans, auto loans or mortgage loans at each zip-code level in a given month. In the final dataset, we have 38886 zip codes in total. Our study aims to evaluate the impacts of Airbnb's entry on mortgage-loan, auto-loan and bankcard-loan delinquencies. We summarize the monthly counts of delinquent behaviors of different loans in Table 1.

[Insert Table 1]

To capture the delinquent decisions of agents who received an income y_{it} at time t, we derive a model to aggregate individual delinquent decisions to zip-code level, by considering strategic and liquidity considerations. Strategic parts include the cost of continuing to make payments versus the cost of default. The liquidity parts include income shock and cash flow by becoming a host on Airbnb. D' denotes the amount of debt to be repaid for next period, and D represents the amount of debt due by the end of current period t. Let's assume a utility function of risk-averse agents as an exponential form, where the degree of risk aversion is captured in exponential coefficient α. The agent i, makes discrete choice at t, and c_0 is a threshold of living at zip-code j.

Without loss of generality, let's assume for a given zip-code j with n agents. The equilibrium of maximum utility of the whole zip-code is multiplied by the utility of each agent i after agent i has maximized her utility function over time t, where $\Phi_{it}(\cdot)$ is the indicator function of delinquency for agent i from time t on. Given an observation period of T, we model the discrete choice model for delinquency decision by pooling and multiplying individual utility functions. We denote c_{it} is a sequence of delinquent decisions agent i who decided to be delinquent at t': $c_{i,t<t'} = 0$, and $c_{i,t' \le t \le T} = 1$.

$$u(c_{it}) = \begin{cases} -e^{-\alpha_i\left(y_{it}+\frac{1}{1+r}D'-D\right)}, & \Phi_{it}\left(y_{it}+\frac{1}{1+r}D'-D \ge c_0\right) \\ -e^{-\alpha_i(y_{it})}, & \Phi_{it}\left(y_{it}+\frac{1}{1+r}D'-D \le c_0\right) = 1 \end{cases}$$

(1) First, every agent i decide which time period t', $t' \in (1,2,\cdots,T)$ to be delinquent $\Phi_{it}(\cdot)$, which maximizes her product of utility function $\Phi_{it}(c_{it})$ over T; (2) Then by multiplying the maximized utility $u^*(c_{it})$ of each agent i, the whole zip-code j reached an equilibrium of financial delinquency path U_j^*; (3) We further restrict that once agent i has been delinquent at t', agent i cannot return to the credit market until the end of observation period T, i.e. $\Phi_{it} = 1,\ t \in (t', t'+1,\cdots,T)$.

$$U_j^*\left(u^*(c_{1t}),\cdots,u^*(c_{nt})\right) = \prod_{i=1}^{n}\left\{\prod_{t=1}^{T}\left[\left(-e^{-\alpha_i\left(y_{it}+\frac{1}{1+r}D'-D\right)}\right)^{(1-\Phi_{it})}\right]\prod_{t=1}^{T}\left[\left(-e^{-\alpha_i(y_{it})}\right)^{\Phi_{it}}\right]\right\}$$

By taking logarithm transformation of the utility function U_j^*, we obtain:

$$\begin{aligned} log\left[U_j^*\left(u^*(c_{1t}),\cdots,u^*(c_{nt})\right)\right] &= \sum_{i=1}^{n}\sum_{t=1}^{T}\left[\alpha_i * \left(y_{it}+\frac{1}{1+r}D'-D\right)\right] \\ &\quad -\sum_{i=1}^{n}\sum_{t=1}^{T}\left[\Phi_{it} * \alpha_i * \left(\frac{1}{1+r}D'-D\right)\right] \\ &\equiv U_j^{equilibrium} \end{aligned}$$

First of all, when agents choose to be delinquent (i.e. $\Phi_{it} = 1$) at t', agents will no longer borrow loans from t' on and the term $\left(\frac{1}{1+r}D'-D\right)$ is irrelevant in the second line of the above equation when $\Phi_{it} = 1$. In addition, we can also observe that the term $\left(y_{it}+\frac{1}{1+r}D'-D\right)$ is the individual-time specific resource constraint, which is denoted as C_{it} hereafter. By re-arranging the equation above, we obtain:

$$\sum_{i=1}^{n}\sum_{t=1}^{T}\left[\alpha_i * \Phi_{it}\left(y_{it}+\frac{1}{1+r}D'-D \le c_0\right)\right] = \sum_{i=1}^{n}\sum_{t=1}^{T}(\alpha_i * C_{it}) + U_j^{equilibrium}$$

As for α_i, we consider two scenarios: First, if α_i is degenerate or α_i has a similar shape of distribution as of C_{it}, it is a trivial case which basically associates the delinquent decision with the individual-time specific liquidity constraint and unobserved fixed effects. Second, in a more realistic perspective, if α_i and C_{it} are both dependent on individual financial and demographic situations such as employment, income, education, willingness to take second mortgage and etc., α_i serves as a weighted factor of social-economic variations of different zip-code j over delinquency.

Let's denote $f(\cdot)$ is a linear function of average income, education and whether the agent has a job, and $g(\cdot)$ is a linear mapping. The individual-time specific resource constraint C_{it} is assumed to be absorbed into social-economic variables X_{it}, time fixed effect λ_t and zip-code fixed effect μ_j.

$$g(\alpha_i * C_{it}) = g\left(f(X_{it}, \lambda_t, \mu_j)\right) = \beta * X_{it} + \lambda_t + \mu_j$$

The entry of Airbnb might affect the income shock from y_{it} to $y_{it}{}' = y_{it} + y_{it}^{airbnb}$ by increasing more agents to hold $\Phi_{it} = 0$ and reducing the regional financial delinquency rate.

$$\sum_{i=1}^{n}\sum_{t=1}^{T}\left[\alpha_i * \Phi_{it}\left(y_{it}{}' + \frac{1}{1+r}D' - D \leq c_0\right)\right]$$
$$= \sum_{i=1}^{n}\sum_{t=1}^{T}\left(\alpha_i * y_{it}^{airbnb}\right) + \sum_{i=1}^{n}\sum_{t=1}^{T}(\alpha_i * C_{it}) + U_j^{equilibrium}$$

We are interested in the effects of income shock from the entry of Airbnb on the original delinquency equilibrium. We would like to estimate the effect from the addition of term $\sum_{i=1}^{n}\sum_{t=1}^{T}\left(\alpha_i * y_{it}^{airbnb}\right)$ on the new left-hand-side equilibrium financial delinquency $\sum_{i=1}^{n}\sum_{t=1}^{T}\left[\alpha_i * \Phi_{it}\left(y_{it}{}' + \frac{1}{1+r}D' - D \leq c_0\right)\right]$, compared to original left-hand-side equilibrium financial delinquency $\sum_{i=1}^{n}\sum_{t=1}^{T}\left[\alpha_i * \Phi_{it}\left(y_{it} + \frac{1}{1+r}D' - D \leq c_0\right)\right]$. The specification sheds light upon the reduced-form Difference-in-Differences model specification.

$$\sum_{i=1}^{n}\sum_{t=1}^{T}\left[\alpha_i * \Phi_{it}\left(y_{it}{}' + \frac{1}{1+r}D' - D \leq c_0\right)\right] = \beta_0 * \sum_{i=1}^{n}\sum_{t=1}^{T}\left(\alpha_i * y_{it}^{airbnb}\right) + \beta_1 * X_{it} + \lambda_t + \mu_j$$

where the left hand side term $\sum_{i=1}^{n}\sum_{t=1}^{T}[\alpha_i * \Phi_{it}(\cdot)]$ captures the zip-code level financial delinquencies, β_0 characterizes the effects of entry of Airbnb, and the other control variables and zip-code fixed effects proxy for the other structures. We utilized the regional delinquent records data and local social-economic variables to estimate the reduced form.

We implement the Difference-in-Differences (DID) given control variables using the equation below:

$$y_{it} = \gamma * D_{it} + \beta_1 * X_{it} + \lambda_t + \mu_i + \varepsilon_{it}$$

where D_{it} is an indicator on whether the Airbnb has entered zip-code i at time t, X_{it} denotes control variables including ratio of high school graduates and higher, number of households, median income, poverty rate, unemployment, ratio of second mortgage at each county, and housing price index at each zip-code level. We denote μ_i, λ_t and ε_{it} respectively as zip-code fixed effects, monthly fixed effects, and i.i.d. random disturbance. γ is the parameter of interest, which measures the causal effects of Airbnb's entry on households' financial delinquencies. We use y_{it} to denote financial delinquencies, including average general delinquent records, auto loan, mortgage loan or bankcard loan delinquencies, at each zip-code level i in month t. Standard errors are clustered at each zip-code level.

5. Empirical Analyses

5.1 Main Results

[Insert Table 2]

As shown in Table 2, the entry of Airbnb significantly reduces the mortgage loan delinquencies by 4.79%, whereas the entry of Airbnb mitigates auto loan delinquencies by 3.27%. The impacts of Airbnb's entry on bankcard loan delinquencies are not significant. The entry of Airbnb significantly reduces the number of delinquencies by 1.58%. In general, we obtain preliminary evidence that the entry of Airbnb would alleviate financial delinquency and improve the financial status of a significant group of households who may have benefited from the income shock brought by the entry of Airbnb.

Furthermore, prior literature has identified three triggering factors for mortgage and auto loan defaults – equity value, income and unemployment. Consistent with the theory prediction, higher median income in a local area will reduce households' delinquency decisions on both auto loans and mortgage loans. The housing price index for each zip code is also negatively associated with financial delinquencies on auto loans and mortgage loans, implying that the higher the value of the property the less likely the homeowners choose to default. Our results also support that unemployment rate positively affects both auto loans and mortgage loans delinquencies.

We also document a positive relationship between the ratio of second mortgages and the likelihood of mortgage-loan and auto-loan defaults. A second mortgage is a lien taken out against the portion of home property that the debtors have paid off, which usually has a higher interest rate. Therefore, a higher ratio of second mortgages suggests severe liquidity constraints for households in a given zip code, and a higher probability of default on mortgage and auto loans.

In order to deal with selection bias that may contaminate our estimated causal effects, we further implement propensity score matching for zip-codes that Airbnb has entered, to find comparable regions with those zip-codes that Airbnb has not entered. By conducting a difference-in-differences analysis with the matched sample, this approach can alleviate the endogeneity concern due to Airbnb's selective entry into certain local areas. Given that the matched zip codes are less likely to exhibit variations in social-economic variables, we can isolate the impact of Airbnb's entry on households' financial delinquencies from changes that are attributable to differential social-economic conditions.

We match a treated zip-code to a zip-code in the control group based on social-economic variables such as Ratio of High School or Higher, No. of Households Log, Median Income, Poverty Ratio, Unemployment Rate, Ratio of Second Mortgage and zip-code level Housing Price Index, before the entry of Airbnb. Before matching, the mean distributions of those variables are statistically different between the treatment group and control group; however, after matching, they are not statistically different. We have implemented propensity score matching 1-to-1 and 1-to-3 to construct our matched samples (See Table 5 for the imbalance check). The estimation results are shown in Table 3 and Table 4.

[Insert Table 3]

[Insert Table 4]

As shown in Table 3, the entry of Airbnb has reduced mortgage loans delinquency by 3.99%. The estimated effects for mortgage delinquencies are the strongest and most significant. As for auto loan delinquencies, our findings suggest that the entry of Airbnb significantly reduces delinquencies on auto loans by 2.68%. We find that Airbnb's entry significantly reduces No. of

Delinquent Records, i.e. total number of mortgage loan, auto loan, and bankcard loan delinquencies, by 0.86%. All effects are statistically significant at 0.01 level. These results show that the financial delinquency alleviation effects due to the entry of Airbnb are both statistically and economically significant.

The estimated results remain robust no matter whether we use propensity score (1-to-1) matched sample or propensity score (1-to-3) matched sample. In Table 4, we show that, using a propensity score (1-to-3) matched sample, the entry of Airbnb has decreased mortgage loan and auto loan delinquencies and No. of Delinquencies by 3.33%, 2.33% and 1.30%, respectively. We provide supportive evidence for H1 and H2 that the entry of Airbnb reduces financial delinquencies on mortgage and auto loans.

As predicted by Dobbie and Song (2020), we argue that the income shock generated by Airbnb's entry mostly affects the financial delinquency of relatively long-term loans, including auto loans and mortgage loans. Liquidity constraints may be more important in the mortgage market, because the delinquent borrowers usually have fewer outside options compared to similar bankcard loan borrowers. Therefore, the liquidity constraints alleviation is less likely to happen to the short-term loans of bankcards. To test H3, we implement difference-in-differences estimation using our matched samples. From the regression results based on both the 1-to-1 and 1-to-3 propensity score matched samples, the effects of Airbnb's entry on bankcard loan delinquencies are statistically insignificant (Column (3) in Table 3 and Column (3) in Table 4), which is consistent with H3. We interpret this result that, although bankcard loans typically are associated with much higher interest rates, debtors are more likely to use proceeds from home-sharing platforms to pay off debts on auto loans and mortgage loans first.

5.2 Impacts of Regulation Policy on Airbnb

The next major question our study examines is the effects of various government regulations implemented by the end of 2019. We collected the pass date and specific requirements of various short-term rentals regulation from governments and media reports. For instance, Portland was the first major city that proposed formal regulations on short-term rentals such as Airbnb listings, as early as 2014. Therefore, we use data from 2014 to 2019, during which we can evaluate the impacts of regulations after regulation policies were implemented in various states in a staggered fashion. San Francisco is another major city that imposed regulation policies on Airbnb as early as in 2015.

In order to register a legal short-term rental, the government of San Francisco requires hosts to be permanent residents of the units (spend at least 275 nights a year), obtain licenses from governments, and only rent up to 90 un-hosted nights per year. In addition, the hosts have to pay additional costs such as short-term rentals license fees, transient occupancy tax and business property tax. Some other cities have also imposed less restrictive regulations, such as Austin and San Diego, where hosts only need to obtain licenses and pay hotel occupation tax. However, some governments such as Chicago and Las Vegas have imposed zoning requirements such that certain areas or buildings may be prohibited from short-term rentals. In July 2016, the City of Chicago proposed a House Share Prohibited Buildings List, outlining buildings excluded from short-term rental activity under the Shared Housing Ordinance.[8] Within the city limits, the City of Las Vegas singled out 3 major prohibited areas where short-term rentals are not allowed to register or operate in 2018.[9]

[Insert Table 6]

We collect those regulation policies on short-term rentals such as Airbnb from city codes or media coverage and categorize them into three broad categories as shown in Table 6. The first category of basic regulations includes license registration, tax and basic apartment restrictions. For instance, regulation authorities usually require owners to submit registration fees and application of operation licenses before legal operations of short-term rentals. In addition, owners need to ensure tax compliance, including hotel occupancy tax and city tax, and meet minimum habitability standards. The second category of regulation is focused on imposing time-limits to short-term rentals wherein specific time-span restrictions on listing periods or listing periods without hosts need to be satisfied. The most restrictive regulation is the third category, categorized as Geo-Location and Prohibitive Regulations. In this type of regulation, local governments set prohibited building lists or prohibited zoning areas, and restrict the number of short-term rental properties in a particular residential area. By doing so, homeowners' access to the platform in certain areas is completely restricted. We estimate how different types of government regulations affect the

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[8] Share Prohibited Buildings List from Chicago Data Portal House (https://data.cityofchicago.org/Buildings/House-Share-Prohibited-Buildings-List/7bzs-jsyj)

[9] Map of Prohibited Areas for Short-term Rentals from official website of City of Las Vegas (http://lasvegas.maps.arcgis.com/apps/OnePane/basicviewer/index.html?appid=1b15b2b28b78488994a7d3d761bd5e0c)

dampening effects brought by Airbnb's entry on financial delinquencies. Again, we use propensity score matching to match the zip codes where regulations are in place with zip codes with no regulations based on the same set of covariates as the matching of Airbnb's entry, including Ratio of High School or Higher, No. of Households Log, Median Income, Poverty Ratio, Unemployment Rate, Ratio of Second Mortgage and zip-code level Housing Price Index. After the propensity score matching, we obtain 337 zip codes with regulations and 935 zip codes without regulations. The imbalance check for the matched treated and control groups can be found in Table 5. The identification strategy to identify general regulation effects on financial delinquencies lies in the equation below:

$$y_{it} = \beta_1 * Entry_{it} + \beta_2 * Entry_{it} * \tau_{it} + \beta_3 * Regulation_{it} + \gamma * X_{it} + \lambda_t + \mu_i + \varepsilon_{it}$$

β_1 captures the average treatment effects of Airbnb's entry. τ_{it} represents the total time periods elapsed since Airbnb's entry, and therefore β_2 identifies a marginal effect of Airbnb's entry at τ periods after Airbnb's entry. We use $Entry_{it}$ and $Entry_{it} * \tau_{it}$ to isolate effects of regulation from effects of Airbnb's entry. β_3, the parameter of interest, estimates the impacts of government regulations on financial delinquencies. We use the equation below to differentiate heterogeneous regulation effects on financial delinquency.

$$y_{it} = \beta_1 * Entry_{it} + \beta_2 * Entry_{it} * \tau_{it} + \sum_{j=1}^{3} \beta_j * Regulation_{ijt} + \gamma * X_{it} + \lambda_t + \mu_i + \varepsilon_{it}$$

We report the results of regulation policy effects in Table 2 to Table 4. After the regulation implemented by local governments, we obtain a positive effect on mortgage loan and auto loan delinquencies and No. of Delinquencies after the regulation. We do not find that regulations have an impact on bankcard loan delinquencies. Our results suggest that after governments start to regulate short-term rentals, the alleviation effects on financial delinquencies brought by home-sharing platforms have been weakened and even offset. As we hypothesized earlier, this result might stem from the negative impact of regulations on hosts' participation in home-sharing platforms. As reported in Column (5) to Column (8) of Table 3, we find that regulations increase mortgage loan and auto loan delinquencies and No. of Delinquencies by 2.90%, 0.73% and 3.65%, respectively.

Regarding the heterogeneous effects of different types of regulation policies, the results are displayed in Table 7. Our results demonstrate that regulation effects on mortgage loan delinquencies are mostly affected by the Geo-Location and Prohibitive Regulations and Basic Regulations. By comparing the regulation effects of various policies on all types of financial delinquencies, we find that Geo-Location and Prohibitive Regulations have the strongest effects. In addition, compared to mortgage loan and auto loan delinquencies, bankcard loan delinquencies are less affected by various types of regulations.

[Insert Table 7]

Given that home-sharing platforms may have affected local communities in a number of ways, economists have warned a broad policy enforcement on regulating home-sharing platforms (Hall et al., 2018). Our study highlights a potential societal cost of such regulations, that is the potential threat to households' financial well-being.

6. Additional Tests

6.1 Heterogeneous Effects Based on Bankruptcy Homestead Exemption Policy

Next, we harness the variation of bankruptcy homestead exemption policy across different states in the United States and estimate the heterogeneous effects of entry of Airbnb on financial delinquency. Since the bankruptcy code in the U.S. has remained stable since 2005, long before the establishment of Airbnb, we consider such policy variations as exogenous to Airbnb's entry.[10]

Since lower bankruptcy homestead exemption values mean that a smaller portion of home property value is protected from selling to creditors. It would motivate individuals to avoid financial delinquency, because households would lose a larger portion of the property value in the case of filing bankruptcies. As shown in Table 8, we examine the heterogeneous effects of Airbnb's entry on financial delinquency in states with lower exemption values and in states with higher exemption values, using the matched samples.

We observe asymmetric magnitude of Airbnb's entry effects. Airbnb's entry in states with higher homestead exemption values, would reduce mortgage loans delinquency by 3.09%, which is

[10] Bankruptcy code is actually uniformly applicable to any state. It is actually the homestead exemption generosity across states that varies. For instance, the exemptions ranged from $0 in New Jersey, to $550,000 in Nevada, to an unlimited amount in Texas. And cross-state differences in generosity have remained relatively stable in the United States in the past two centuries (Indarte, 2019).

statistically significant at the 0.1 level. In those states with lower bankruptcy exemption values, Airbnb's entry reduces mortgage loans delinquency by 8.27%, statistically significant at the 0.01 level. As for auto loan delinquencies, the entry of Airbnb significantly reduces auto loans delinquency by 8.52%, in those states with lower homestead exemption values. By contrast, the dampening effect of Airbnb's entry on auto loan delinquency is 2.28% in states with higher homestead exemption values, which is smaller in magnitude than that in states with lower homestead exemption values and is not statistically significant. Again, we find that Airbnb's entry does not significantly affect bankcard loan delinquencies which is consistent with our findings earlier.

[Insert Table 8]

These results suggest that the entry of Airbnb brings a greater impact on reducing financial delinquencies in states with lower homestead exemption values. This is because after Airbnb's entry, homeowners have another option to list their properties on home-sharing platforms to generate extra income and make ends meet, rather than default on mortgage loans or filing for bankruptcies. In contrast, in states with extremely high exemption values, financially distressed individuals may remain financially delinquent simply because in the worst scenario of bankruptcy, they can still keep their home property. In this case, they have less incentive to participate on home-sharing platforms and thus less likely to benefit from the income shocks brought by Airbnb's entry.

Similarly, our results suggest that the positive income shock brought by home-sharing platforms would also help households to repay the monthly auto loans in states with various homestead exemption values. This is consistent with prior literature that both mortgage and auto loans delinquencies are mostly caused by liquidity constraints, negative income shock or a job loss.

[Insert Table 9]

In Table 9, we show heterogeneous effects of regulation based on homestead exemption values. The results are consistent with Table 8, that the effects are mostly significant in states with lower homestead exemption values. However, for mortgage delinquencies, effects of regulation are significant in states with higher homestead exemption values. Consistent with our intuition, people in states with higher homestead exemption values are more likely to file bankruptcies in which case they could still keep a larger portion of their properties. Therefore, the restricted access to home-sharing platforms resulted from regulations will likely lead to a higher impact on mortgage delinquencies in those states.

6.2 Parallel Trends

In order to validate the difference-in-differences analysis, the treatment group and control group should satisfy the parallel trend assumption such that prior to Airbnb's entry, both groups exhibit similar trends in the outcome variables. Therefore, if absent the treatment, the financial delinquency behavior of these two groups would have moved parallelly. We test the parallel trend hypothesis using the relative time model below:

$$y_{it} = \left(\sum_{\tau=-6}^{\tau=6} \eta_\tau * I\left(m_{i,t} = \tau\right)\right) * D_{i,t} + \beta * X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}$$

where $m_{i,t}$ denotes number of months before or after the month when Airbnb entered into zip-code i, and $I(\cdot)$ is an indicator function that equals to 1 if the condition is met and equals to 0 otherwise. We also include all control variables, monthly fixed-effects and zip-code fixed effects.

As shown in Table 10, the coefficients from Airbnb Entry Lag 6 to Airbnb Entry Lag 1 are not statistically significant in mortgage-loan, auto-loan and bankcard-loan delinquencies. After Airbnb's entry, mortgage loan delinquencies drop significantly, and the sign of auto loan delinquency turns negative immediately. Therefore, we demonstrate that the trends of the control group and treatment group before Airbnb's entry are parallel, which supports our parallel trend assumption and thus the validity of our control group.

We report the results of relative time model of regulation in Table 11. We do not find a systematic pattern of mortgage loan and auto loan delinquencies in the pre-regulation periods. However, after the regulations begin, coefficients of regulation effects become significantly positive. Therefore, we support the parallel trend assumption of difference-in-differences analysis in regulation effects.

[Insert Table 10]

[Insert Table 11]

7. Dynamic Effects of Airbnb's Entry on Delinquencies

We further investigate the potential endogenous financial delinquency decisions among mortgage loans, auto loans and bankcard loans as a whole. There are three reasons that we would like to further explore the dynamic structures among different types of credit defaults.

First of all, most U.S. households own at least one type of loans, and face financial delinquency decisions among multiple liquidity constraints of different loans. In terms of monthly payments, bankcard loans have less monthly payment, followed by auto loans, and mortgage loans. As for the cost of delaying payments, bankcard loans have the highest annual interest rate, followed by auto loans and mortgage loans. In this case, households with multiple liquidity constraints, may encounter an endogenous decision process on which loans to pay first, and how to manage their cash flow over a short-term time period. We cannot ignore such endogenous financial resources allocation, when studying the effects of income shocks on zip-code level financial delinquency. Rios-Solis et al. (2017) study the repayment policy when debtors are faced with multiple loans, by proposing an optimization model that minimizes the total amount of cash required to repay the loans. Gathergood et al. (2019) study debt repayment behaviors of 1.4 million individuals in the United Kingdom across multiple credit cards, and find that repayments are not allocated to cards with higher interest rates, but in proportion to balances of multiple cards. Amar et al. (2011) examine the hypothesis of debt account aversion and find that debtors consistently pay off small debts first even though the larger debts have higher interest rates. By comparing the concentration strategy with the dispersed strategy, Kettle et al. (2016) find that concentrating payments entirely into one debt account tends to motivate consumers to be debt free, leading them to repay their debts more aggressively. Our research contributes to the investigation on how households allocate the extra income to pay off debts across bankcard, auto loans and mortgage loans, when facing the income shock from Airbnb’s entry.

In addition, we could further verify the impact of Airbnb's entry on financial delinquencies and model the effects on various types of delinquencies in a more simultaneous way. By jointly modeling financial delinquencies and treating Airbnb's entry as an exogenous variable in a Vector Autoregressive Model (VAR) framework, we obtain further evidence supporting the impact of Airbnb’s entry on reducing financial delinquencies. By studying the lead-lag structure of various delinquency behaviors, we can gain further insights into the impacts of Airbnb’s entry to households’ financial decision making process.

Last but not the least, the Vector Autoregressive Model is one of the most important toolboxes in studying shocks in macroeconomics and can provide some policy implications based on an impulse-response analysis for the dynamic causal structure. We exploit information from the panel structure at each zip-code level, and conduct analysis by estimating a Panel Vector Autoregressive Model (PVAR) as below.

$$\begin{pmatrix} mortgage_{i,t} \\ auto_{i,t} \\ bankcard_{i,t} \end{pmatrix} = \begin{pmatrix} \theta_{1,1} & \theta_{1,2} & \theta_{1,3} \\ \theta_{2,1} & \theta_{2,2} & \theta_{2,3} \\ \theta_{3,1} & \theta_{3,2} & \theta_{3,3} \end{pmatrix} \begin{pmatrix} mortgage_{i,t-1} \\ auto_{i,t-1} \\ bankcard_{i,t-1} \end{pmatrix} + \begin{pmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \end{pmatrix} \cdot Entry_{i,t} + \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} \cdot X_{i,t} + \varepsilon_{it}$$

This model estimates a Lag structure of mortgage loan, auto loan and bankcard loan delinquencies in a Panel VAR model using our matched sample. To determine the optimal order of lags of Panel VAR model, we calculate MMSC-BIC according to the model selection criteria proposed by Andrews and Lu (2001), and specify the model at an order of 2 in both exogeneous entry model and endogenous entry model. In addition, the lag order of 2 is adopted in estimating liquidity and the dynamics of house prices, as a consistent estimator to avoid incidental parameter problem (Nickell, 1981; Head et al., 2014). In this primary model, we include Airbnb's entry and all control variables in Section 5 as exogeneous regressors. Note that we relax the restriction on the independence assumption across various types of loan delinquency and allow the default rate of a specific loan in the current period to depend on the default rate of itself and the other two types of loans in the past one or two periods. We estimate the exogeneous impacts of Airbnb's entry on three types of loans' default (i.e. γ_1, γ_2 and γ_3) respectively, after allowing the autocorrelation of a specific ($\theta_{1,1}, \theta_{2,2}$ and $\theta_{3,3}$) and cross-correlation among other loans (i.e. $\theta_{1,2}, \theta_{1,3}, \theta_{2,1}, \theta_{2,3}$, $\theta_{3,1}$ and $\theta_{3,2}$). We also control for the time-varying zip-code level housing price index in all models.

[Insert Table 12]

We first estimate the pilot model based on the matched sample without social-economic confounding factors. Table 12 shows the results of PVAR models with Lag 2 specifications. We find that the impact of Airbnb's entry on mortgage loans delinquencies remains robust and significant. Airbnb's entry significantly reduces mortgage delinquencies by 3.51%. Consistent with our reduced-form estimation and hypothesis, the effects of Airbnb's entry on bankcard loan delinquencies are not significant. Taken together, in this joint model of mortgage, auto loan and bankcard loan delinquencies, we again find supportive evidence for the dampening effects of Airbnb's entry on financial delinquencies. We can observe that even if we estimate the Lag 2 structure of three types of financial delinquencies, and at the same time control all social-economic variables, the impact of Airbnb's entry on the mortgage loans delinquency is still statistically significant at the 0.01 level. The magnitude is also very close to our reduced-form estimation, i.e. 3.99%. By taking into account all Lag-2 terms of financial delinquencies and social-economic variables, the effects of Airbnb's entry on auto loan and bankcard loan delinquencies are insignificant.

Airbnb's entry is deemed as an exogenous shock in the previous models. As a robustness check, we further relax the assumption that the entry of Airbnb is exogeneous to the current and past financial delinquencies in a region. The motivation is twofold. First of all, by relaxing this assumption, we could explore the dynamic structure of the endogenous entry of Airbnb, and mortgage, auto loan and bankcard loan delinquencies. Second, by treating Airbnb's entry as an endogenous variable, we can provide policy simulations for the loss in counterfactual settings wherein governments were to regulate or subsidize Airbnb at a given location. Thus, we specify the Panel VAR model as shown below:

$$\begin{pmatrix} mortgage_{i,t} \\ auto_{i,t} \\ bankcard_{i,t} \\ entry_{i,t} \end{pmatrix} = \begin{pmatrix} \theta_{1,1} & \theta_{1,2} & \theta_{1,3} & \theta_{1,4} \\ \theta_{2,1} & \theta_{2,2} & \theta_{2,3} & \theta_{2,4} \\ \theta_{3,1} & \theta_{3,2} & \theta_{3,3} & \theta_{3,4} \\ \theta_{4,1} & \theta_{4,2} & \theta_{4,3} & \theta_{4,4} \end{pmatrix} \begin{pmatrix} mortgage_{i,t-1} \\ auto_{i,t-1} \\ bankcard_{i,t-1} \\ entry_{i,t-1} \end{pmatrix} + \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{pmatrix} \cdot X_{i,t} + \varepsilon_{it}$$

The estimation results are shown in Table 13. We specify Lag 2 structures to endogenously model mortgage delinquencies, auto loan delinquencies, bankcard loan delinquencies as well as the entry of Airbnb, with zip-code level control variables such as the Housing Price Index. From Table 13, we can see that Airbnb's entry significantly reduces mortgage loan delinquencies by 3.60% at the 99% confidence level. Consistent with our previous results, Airbnb's entry does not have a significant impact on bankcard loan delinquencies.

[Insert Table 13]

Taking together, these results provide further supportive evidence for the dampening effects of Airbnb's entry on financial delinquencies.

7.1 Impulse-Response Analysis on Loan Delinquencies and Airbnb's Entry

In this section, we further conduct the impulse-response analysis and obtain policy implications based on the dynamic structure we have estimated earlier. Orthogonal impulse-response functions are used to causally interpret the recursive structure of Panel VAR models.

First, we increase the percentage of Airbnb's entry by one unit of standard deviation, which can be considered as a counterfactual simulation that governments encourage adoption of Airbnb. As shown in Figure 1, all mortgage delinquencies, auto loan delinquencies and bankcard loan delinquencies respond negatively to the increase of Airbnb entry for 50 time periods. In terms of scale, the mortgage loan delinquencies decrease the most, followed by auto loan delinquencies and bankcard loan delinquencies.

Further, we impose a shock on mortgage loan, auto loan and bankcard loan delinquencies, respectively. The results are shown in Figure 2, Figure 3 and Figure 4. All impulse-response analyses last for a 50-month observation period and the confidence intervals are obtained with a 200-time Monte Carlo Simulation from the distribution of the fitted Panel VAR model. If we impose a positive impulse shock on mortgage loan delinquencies by one unit of standard deviation, the bankcard loan delinquencies and auto loan delinquencies will increase significantly, and the response of bankcard loan delinquencies is stronger. If we impose a positive shock on auto loan delinquencies by one unit of standard deviation, the bankcard loan delinquencies decrease significantly at first, and gradually return to 0; the mortgage loan delinquencies do not respond significantly in the time window. If the positive shock is imposed on bankcard loan delinquencies, we observe that both auto loan and mortgage delinquencies respond significantly in a positive direction, and the response of mortgage loan delinquencies is stronger.

We can infer from the results how the households prioritize monthly repayments and decisions to default. If the default rate of mortgage loans increases, it will be contagious and lead to higher likelihood of bankcard loan and auto loan delinquencies. As the mortgage loans are prioritized among many households, the default for mortgage loans usually implies a severe negative liquidity shock, which leads to debt overhang. However, the increase of auto loan delinquencies is a nuanced case. On one hand, it also implies the negative liquidity shock is likely to increase the mortgage loan delinquencies. On the other hand, households that default on auto loans can provide the liquidity for bankcard loans which were used for repaying the auto loans for a short time, leading to decreasing delinquencies of bankcard loans temporarily. The increase of bankcard loan delinquencies usually occurs among the low-income households during adverse events like job loss, which also lead to an increase in auto loan and mortgage loan delinquencies.

8. Implications

Our study offers several managerial implications. First, we provide evidence that the risk of mortgage delinquencies can be alleviated by participating in home-sharing platforms, which helps relax hosts' liquidity constraints. We find that Airbnb's entry reduces mortgage delinquencies by 3.99%, and auto-loan delinquencies by 2.68%. Such findings are consistent with the "double trigger" hypothesis in the household finance literature, viz. the co-occurrence of liquidity shock and negative equity triggers mortgage defaults. In the United States, about 1% of households file bankruptcy each year, leading to one million filings and $188.9 billion in debt forgiveness to households (Indarte, 2019). Therefore, a 3.99% reduction of mortgage delinquencies translate to $7.556 billion dollars saved. Moreover, the negative externalities and downstream effects of financial defaults on the housing market, labor market and credit market, are beyond measure. Our research also provides evidence on how households allocate liquidity to repay multiple loans. In face of multiple loans, households usually repay the mortgage first, and make a tradeoff between auto loans and bankcard loans. The finding that the liquidity shock resulted from Airbnb does not reduce these three types of financial delinquencies evenly or simultaneously is consistent with the "credit card debt puzzle": consumers simultaneously hold high-interest credit card debts and liquid assets, which could have been used to repay the credit card debt.

Secondly, policymakers shall take into account the economic and social costs when regulating home-sharing platforms. Our findings suggest that the cost of regulating home-sharing platforms is significant if policymakers consider the reduction in financial delinquencies brought by home-sharing platforms. After regulating home-sharing platforms, the dampening effects of Airbnb's entry on financial delinquencies are weakened or offset, especially on mortgage loans. Our study provides the very first evidence on the economic effects of regulations, as prior studies which typically investigate the effectiveness of one specific regulation have found mixed results. For example, licensing protects consumers from low-quality service providers. However, license holders may exert pressure to public authorities to exclude new entrants from the market, leading to increased barriers of entry (Edelman and Geradin, 2016). By contrast, another study documents that “One Host, One Home” policy benefits platforms, resulting in higher revenue and supply from nonprofessional hosts (Chen, et al. 2020). In addition, our study does not focus on a specific regulation policy. Instead, we estimate the impacts of various types of regulations on the local communities. On average, regulations enforced by local governments would elevate the entry barrier for individual suppliers, restrict homeowners’ access to home-sharing platforms and hence their ability to generate supplementary income. These regulations not only affect homeowners, but also may have impacts on other industries such as tourism, restaurants, hospitality, leisure industries and so on. Even though we quantify the direct cost of regulating home-sharing platforms on financial delinquencies, the indirect effects on those other industries, are beyond measure (Leick et al., 2020). Considering all potential downstream impacts, the cost of regulating home-sharing platforms may be amplified.

In light of hosts’ improved financial well-being brought by home-sharing platforms, our study speaks to the recent call from the academic community for a more flexible framework for regulating home-sharing platforms. A desirable regulation policy not only protects suppliers and consumers in this industry, but also preserves efficiencies brought by these home-sharing platforms. While platforms are capable of ensuring a competitive and fair market, government regulators are better suited to implement interventions to ensure fire safety arrangements, minimum pay, working conditions, and service to low-income users and racial minorities. The objective of regulating home-sharing platforms should focus on correcting market failures rather than excluding entrants (Edelman and Geradin, 2016). Policymakers could also tailor local regulations for home-sharing platforms based on locations and property types. For instance, regulators could coordinate with home-sharing platforms, and encourage organizations such as homeowner associations of apartment buildings, to resolve issues such as negative externalities exerted on neighborhoods (Cohen and Sundararajan, 2015; Edelman and Geradin, 2016; Filippas and Horton, 2020). In addition, there is some space left for the coordination between home-sharing platforms and local governments. For example, the cooperation can also result in tailored regulations such as tax compliance through voluntary collection agreement, which Airbnb has adopted since 2014.[11]

Given the high penetration rate of gig workers or sharing economy participants, even though we focus on Airbnb, our findings have implications for other sharing economy platforms. According to a report of Economic Well-Being of the U.S. Households in 2017 from the Federal Reserve,[12] three in ten adults participated in the gig economy, although as a supplemental source of income. Two in five gig workers are doing these side jobs in addition to their main jobs; however, an additional 16% of gig workers live on gig economy as their primary income. This evidence implies that the impact of the sharing economy cannot be simply interpreted as changes in the composition of labor force. Rather, the impacts go beyond that, and for the large share of households who might struggle with unexpected expenses or liquidity constraints, sharing economy may have provided them a viable livelihood.

9. Conclusion and Discussion

In this study, we implement the Difference-in-Differences analysis on a matched sample, to quantify the effects of Airbnb's entry on mortgage, auto loan and bankcard loan delinquencies. Airbnb's entry reduces mortgage loan delinquencies by 3.99% and auto loan delinquencies by 2.68%, but it does not significantly affect bankcard loan delinquencies. We provide a battery of robustness checks to resolve concerns on the endogeneity. In addition, we also derive a structure model based on assumptions such as agents' risk aversion and obtain an equilibrium model which guides the reduced-form estimation of income shocks on financial delinquencies. We leverage the variation in the state-wise bankruptcy homestead exemption levels and verify that the impacts of Airbnb's entry on alleviating delinquencies are greater in states with lower homestead exemption.

Our results also provide supporting evidence that regulation policies on home-sharing platforms like Airbnb would weaken the delinquency dampening effects brought by Airbnb's entry. Among

[11] To date, Airbnb has delivered more than $3.4 billion to local governments around the world in the past seven years. Airbnb first began collecting and remitting taxes on behalf of the host community in 2014 through voluntary collection agreements with San Francisco, California and Portland, Oregon. Now, the platform collects tax in 30,000 jurisdictions around the world and the number continues to grow.

[12] https://www.federalreserve.gov/publications/files/2017-report-economic-well-being-us-households-201805.pdf

the three types of regulations, mortgage delinquencies are mostly affected by the Geo-Location and Prohibitive Regulations and followed by Basic Regulations and Time-Limit Regulations. Further, we jointly model mortgage, auto loan and bankcard loan delinquencies with a Panel VAR model, to further validate the impact of Airbnb's entry on financial delinquencies.

Our study is not without limitations. First of all, to the best of our knowledge, we are among the first studies which leverage the highly granular zip-code level data, to derive the causal estimation on the impact of home-sharing platforms' entry and the subsequent regulations on those platforms on household financial delinquencies. However, we are not able to observe demographics or financial situation for each household, and their activities on the home-sharing platforms. Pending the availability of such data, it would be of great interest to extend this research to a household level and explore the heterogeneous impacts of liquidity expansion on household financial decisions, such as in Cookson et al. (2019). The second limitation is on the possible lagged effects of some macroeconomic events on household defaults, such as the financial crisis and fracking boom, which may coincide with the entry of Airbnb. However, our DID estimates rest on the parallel trend assumption and include extensive control variables to isolate Airbnb's entry from other possible confounders. Overall, our results remain highly robust and consistent with the theory prediction from the literature. Last but the least, our study does not distinguish individual investors from institutional investors on those home-sharing platforms. We assume that the dampening effects are mostly likely to benefit individual investors. In this case, our estimated effects might be even larger after excluding institutional investors.

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Impacts of the Sharing Economy Entry and Regulations on Financial Delinquencies

1 Appendix A: Tables and Figures

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Auto Loan	2,616,257	11.5032	50.5726	0	367
Bankcard Loan	3,023,499	28.0871	50.5728	0	1394
Mortgage Loan	2,611,370	15.7591	27.2626	0	843
High School or Higher (%)	1,970,804	87.6986	5.2112	61.4000	98.5000
No. of Households (Log)	1,971,196	11.8708	1.1788	9.7380	15.0136
Median Income	1,971,196	78982.7700	181147.2000	20335	3313908
Poverty Rate (%)	1,971,196	14.7451	5.2677	1.5000	55.9000
Unemployment Rate (%)	1,967,690	8.0115	3.0677	1.1000	26.0000
Ratio of Second Mortgage (%)	1,961,634	16.7421	5.7268	0.9000	36.3000
Housing Price Index	1,346,537	136.0541	31.3512	39.9100	525.6600

Notes: The data contains monthly records from January 2010 to December 2016. The socio-economic variables are extracted from American Community Survey (ACS) and the zipcode-level price index are from Federal Housing Finance Agency (FHDA).

Table 2: Effects of Airbnb's Entry and Regulations on Mortgage Loans, Auto Loans, Bankcard Loans and No. of Delinquent Records

	(1) Mortgage Loans	(2) Auto Loans	(3) Bankcard Loans	(4) No. Delinquencies	(5) Mortgage Loans	(6) Auto Loans	(7) Bankcard Loans	(8) No. Delinquencies
Entry of Airbnb	-0.0479***	-0.0327***	0.0049	-0.0158***	-0.0475***	0.0024*	0.0214***	-0.0237***
	(0.0100)	(0.0093)	(0.0059)	(0.0029)	(0.0067)	(0.0013)	(0.0054)	(0.0070)
Entry of Airbnb $\times$ τ	–	–	–	–	0.0026***	-0.0004***	-0.0029***	-0.0008*
	–	–	–	–	(0.0005)	(0.0001)	(0.0004)	(0.0005)
Regulation	–	–	–	–	0.0385***	0.0023**	0.0012	0.0421***
	–	–	–	–	(0.0050)	(0.0010)	(0.0043)	(0.0055)
High School or Higher	0.0061***	0.0028**	0.0005	0.0005	0.0010**	0.0002	0.0027***	0.0038***
	(0.0011)	(0.0012)	(0.0008)	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0006)
No. of Households Log.	-0.4620***	-0.0652	0.3160***	-0.2020***	-0.0810***	0.0031	-0.0087	-0.0865**
	(0.0600)	(0.0628)	(0.0471)	(0.0218)	(0.0281)	(0.0079)	(0.0216)	(0.0355)
Median Income	-0.0012**	-0.0020***	-0.0011**	-0.0013***	-0.0000***	-0.0000***	0.0000***	-0.0000***
	(0.0006)	(0.0006)	(0.0004)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Poverty Rate	0.0027***	-0.0025***	-0.0008	-0.0001	-0.0005	-0.0005***	-0.0011***	-0.0021***
	(0.0008)	(0.0009)	(0.0007)	(0.0003)	(0.0003)	(0.0001)	(0.0003)	(0.0005)
Unemployment Rate	0.0170***	0.0124***	0.0081***	-0.0010***	0.0099***	0.0001	-0.0025***	0.0075***
	(0.0011)	(0.0011)	(0.0008)	(0.0004)	(0.0005)	(0.0002)	(0.0004)	(0.0007)
Second Mortgage	0.0109***	0.0079***	0.0035***	-0.0011***	0.0045***	0.0002**	0.0009***	0.0056***
	(0.0006)	(0.0006)	(0.0004)	(0.0002)	(0.0003)	(0.0001)	(0.0002)	(0.0004)
Housing Price Index	-0.0083***	-0.0033***	-0.0016***	-0.0013***	-0.0009***	0.0001***	0.0005***	-0.0003***
	(0.00012)	(0.0001)	(0.0001)	(4.49e-05)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Constant	8.7830***	3.5060***	-0.1430	5.6580***	1.2537***	0.0316	0.3725	1.6578***
	(0.7210)	(0.7560)	(0.5630)	(0.2600)	(0.3363)	(0.0957)	(0.2608)	(0.4274)
Observations	922,257	902,348	931,934	935,802	220,649	220,649	220,649	220,649
R-squared	0.947	0.931	0.965	0.978	0.8377	0.7127	0.8179	0.8784
Zipcode Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1), and are clustered at each zipcode level.

Table 3: Effects of Airbnb's Entry and Regulation on Mortgage Loans, Auto Loans, Bankcard Loans and No. of Delinquencies (1-to-1 Propensity Score Matching)

	(1) Mortgage Loans	(2) Auto Loans	(3) Bankcard Loans	(4) No. Delinquencies	(5) Mortgage Loans	(6) Auto Loans	(7) Bankcard Loans	(8) No. Delinquencies
Entry of Airbnb	-0.0399***	-0.0268***	-0.0028	-0.0086***	-0.0625***	0.0063**	0.0257**	-0.0305**
	(0.0104)	(0.0103)	(0.0066)	(0.0031)	(0.0137)	(0.0029)	(0.0115)	(0.0146)
Entry of Airbnb × τ	–	–	–	–	0.0013	-0.0005***	-0.0013	-0.0006
	–	–	–	–	(0.0010)	(0.0002)	(0.0008)	(0.0010)
Regulation	–	–	–	–	0.0290***	0.0073***	0.0002	0.0365***
	–	–	–	–	(0.0081)	(0.0016)	(0.0072)	(0.0086)
High School or Higher	0.0145***	-0.0035	-0.0033	0.0040***	0.0060*	0.0005	0.0069**	0.0133***
	(0.0041)	(0.0042)	(0.0029)	(0.0013)	(0.0035)	(0.0008)	(0.0028)	(0.0041)
No. of Households Log.	-0.5000**	-0.3050	0.0865	-0.1260*	0.5373***	-0.1175*	-0.5587***	-0.1390
	(0.2280)	(0.2170)	(0.1540)	(0.0665)	(0.1518)	(0.0342)	(0.1275)	(0.1687)
Median Income	-0.0054***	-0.0070***	-0.0025**	-0.0046***	-0.0000***	-0.0000***	0.0000***	-0.0000
	(0.0017)	(0.0018)	(0.0011)	(0.0005)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Poverty Rate	-0.0037	-0.0106***	-0.0079***	-0.0014	-0.0001	-0.0008	-0.0033*	-0.0042*
	(0.0033)	(0.0033)	(0.0024)	(0.0009)	(0.0019)	(0.0006)	(0.0019)	(0.0025)
Unemployment Rate	0.0265***	0.0081*	0.0040	-0.0040***	0.0227***	0.0007	-0.0039	0.0195***
	(0.0041)	(0.0042)	(0.0029)	(0.0012)	(0.0033)	(0.0011)	(0.0035)	(0.0046)
Second Mortgage	0.0244***	0.0134***	0.0095***	-0.0036***	0.0003	0.0004	0.0039***	0.0046**
	(0.0020)	(0.0020)	(0.0014)	(0.0006)	(0.0016)	(0.0005)	(0.0014)	(0.0020)
Housing Price Index	-0.0064***	-0.0022***	-0.0012***	-0.0013***	-0.0005**	0.0000	0.0003	-0.0002
	(0.0003)	(0.0003)	(0.0002)	(8.41e-05)	(0.0002)	(0.0000)	(0.0002)	(0.0002)
Constant	9.2600***	7.7680***	3.3660*	4.8870***	-7.4103***	1.5963***	7.3672***	1.5532
	(3.0410)	(2.8810)	(2.0370)	(0.8750)	(2.0598)	(0.4608)	(1.7188)	(2.3316)
Observations	142,442	140,256	142,903	143,028	12,332	12,332	12,332	12,332
R-squared	0.949	0.937	0.971	0.986	0.8966	0.8663	0.8990	0.9445
Zipcode Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1), and are clustered at each zipcode level.We matched treatment and control units based on all control variables including *High School or Higher*, *No. of Households Log.*, *Median Income*, *Poverty Rate*, *Unemployment Rate*, *Ratio of Second Mortgage*, and *Housing Price Index*.

Table 4: Effects of Airbnb's Entry and Regulation on Mortgage Loans, Auto Loans, Bankcard Loans and Delinquent Records (1-to-3 Propensity Score Matching)

	(1) Mortgage Loans	(2) Auto Loans	(3) Bankcard Loans	(4) No. Delinquencies	(5) Mortgage Loans	(6) Auto Loans	(7) Bankcard Loans	(8) No. Delinquencies
Entry of Airbnb	-0.0333***	-0.0233**	0.0036	-0.0130***	-0.0609***	0.0060**	0.0304***	-0.0245*
	(0.0101)	(0.0099)	(0.0062)	(0.0030)	(0.0126)	(0.0027)	(0.0110)	(0.0133)
Entry of Airbnb $\times$ τ	–	–	–	–	0.0027***	-0.0006***	-0.0018**	0.0003
	–	–	–	–	(0.0008)	(0.0001)	(0.0007)	(0.0008)
Regulation	–	–	–	–	0.0241***	0.0072***	0.0051	0.0364***
	–	–	–	–	(0.0079)	(0.0016)	(0.0072)	(0.0085)
High School or Higher	0.0116***	-0.0031	-0.0027	0.0036***	0.0074***	0.0010*	0.0081***	0.0166***
	(0.0032)	(0.0031)	(0.0022)	(0.0011)	(0.0025)	(0.0006)	(0.0019)	(0.0030)
No. of Households Log.	-0.8960***	-0.4130**	0.1740	-0.1390**	0.3348***	-0.0943***	-0.3319***	-0.0913
	(0.1720)	(0.1640)	(0.1210)	(0.0540)	(0.1211)	(0.0289)	(0.1000)	(0.1378)
Median Income	-0.0021	-0.0054***	-0.0015*	-0.0038***	-0.0000***	-0.0000***	0.0000***	-0.0000
	(0.0013)	(0.0014)	(0.0008)	(0.0004)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Poverty Rate	0.0023	-0.0093***	-0.0056***	-0.0006	0.0015	-0.0011**	-0.0026*	-0.0022
	(0.0025)	(0.0025)	(0.0018)	(0.0007)	(0.0015)	(0.0005)	(0.0013)	(0.0020)
Unemployment Rate	0.0257***	0.0109***	0.0078***	-0.0038***	0.0251***	0.0006	-0.0054**	0.0203***
	(0.0029)	(0.0031)	(0.0021)	(0.0010)	(0.0027)	(0.0007)	(0.0024)	(0.0036)
Second Mortgage	0.0212***	0.0133***	0.0070***	-0.0030***	0.0045***	0.0007*	0.0027**	0.0079***
	(0.0015)	(0.0016)	(0.0011)	(0.0005)	(0.0013)	(0.0004)	(0.0012)	(0.0018)
Housing Price Index	-0.0073***	-0.0025***	-0.0014***	-0.0014***	-0.0007***	0.0001***	0.0007***	0.0002
	(0.0003)	(0.0002)	(0.0001)	(7.20e-05)	(0.0002)	(0.0000)	(0.0001)	(0.0002)
Constant	14.3300***	8.9060***	2.0650	4.9830***	-4.8843***	1.2194***	4.1443***	0.4794
	(2.2410)	(2.1470)	(1.5670)	(0.6940)	(1.6091)	(0.3951)	(1.3350)	(1.8602)
Observations	226,715	222,540	227,720	228,228	20,476	20,476	20,476	20,476
R-squared	0.952	0.938	0.972	0.985	0.8814	0.8414	0.8916	0.9333
Zipcode Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1), and are clustered at each zipcode level. We matched treatment and control units based on all control variables including *High School or Higher*, *No. of Households Log.*, *Median Income*, *Poverty Rate*, *Unemployment Rate*, *Ratio of Second Mortgage*, and *Housing Price Index*.

Table 5: Balance Check of Propensity Score Matching

	Before Matching		After Matching	
Variable	t-statistic	p-value	t-statistic	p-value
DV (Entry)				
High School or Higher (%)	-19.40	0.000	0.89	0.371
No. of Households Log	41.07	0.000	0.64	0.520
Median Income	6.04	0.000	-0.47	0.638
Poverty Rate (%)	6.83	0.000	0.80	0.422
Unemployment Rate (%)	2.72	0.007	0.06	0.949
Ratio of Second Mortgage (%)	11.86	0.000	0.89	0.371
Housing Price Index	24.08	0.000	-1.40	0.163
DV (Regulation)				
High School or Higher (%)	-31.40	0.000	-0.42	0.678
No. of Households Log	47.40	0.000	0.59	0.558
Median Income	-0.90	0.365	0.01	0.995
Poverty Rate (%)	15.88	0.000	0.62	0.538
Unemployment Rate (%)	10.31	0.000	1.16	0.248
Ratio of Second Mortgage (%)	-0.51	0.608	1.75	0.080
Housing Price Index	47.41	0.000	-1.50	0.135

Notes: The socio-economic variables are extracted from American Community Survey (ACS) and the zipcode-level price index are from Federal Housing Finance Agency (FHDA).

Table 6: Brief Summary of Representative Regulations

City	Summary	Since	Tax Cost
New York	Host Present & No Ads & Up to 2 Paying Guests	May 2011	Sales and Use Tax & Hotel Occupancy Tax
San Francisco	Registration & Up to 90 nights without hosts	February 2015	Transient Occupancy Tax & Biz Personal Property Tax
Los Angeles County	License & Up to 120 Days Per Year	September 2015	Transient Occupancy Tax
Chicago	License & Prohibited Building List	July 2016	Hotel Occupancy Tax
Austin	License, Cap of STR within each census tract	February 2016	Hotel Occupancy Tax
Seattle	Cap of No. of Listings at difference places	September 2017	Seattle city tax
New Orleans	License, Zoning Ordinance, 90 nights/ year	April 2017	Short-term rental tax
Portland	License, occupy 9 months/year, primary residence	Since 2014	lodging tax, business tax and city tax
San Diego	Tax & Tourist Marketing District Assessment	September 2016	Transient Occupancy Tax

Table 7: Heterogeneous Policy Impacts of Airbnb on Financial Delinquency

	(1) Mortgage Loan	(2) Auto Loan	(3) Bankcard Loan	(4) Delinquencies
Entry of Airbnb	-0.0612***	0.0062**	0.0319***	-0.0231*
	(0.0126)	(0.0027)	(0.0108)	(0.0132)
Entry of Airbnb × τ	0.0027***	-0.0006***	-0.0019***	0.0002
	(0.0008)	(0.0001)	(0.0007)	(0.0008)
Basic Regulation	0.0268**	0.0081***	0.0039	0.0389***
	(0.0105)	(0.0028)	(0.0099)	(0.0135)
Geo-Location and Prohibitive Regulation	0.0205**	0.0090***	0.0205*	0.0501***
	(0.0091)	(0.0020)	(0.0106)	(0.0116)
Time-Limit Regulation	0.0294	-0.0032	-0.0534***	-0.0271
	(0.0202)	(0.0028)	(0.0101)	(0.0193)
High School or Higher	0.0075***	0.0010	0.0078***	0.0163***
	(0.0025)	(0.0006)	(0.0019)	(0.0030)
No. of Households Log	0.3440***	-0.1000***	-0.3764***	-0.1325
	(0.1229)	(0.0296)	(0.1009)	(0.1396)
Median Income	-0.0000***	-0.0000***	0.0000***	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Poverty Ratio	0.0015	-0.0011**	-0.0025*	-0.0021
	(0.0015)	(0.0005)	(0.0014)	(0.0020)
Unemployment Rate	0.0252***	0.0005	-0.0060**	0.0197***
	(0.0027)	(0.0007)	(0.0024)	(0.0036)
Ratio of Second Mortgage	0.0044***	0.0007*	0.0028**	0.0079***
	(0.0014)	(0.0004)	(0.0012)	(0.0018)
Housing Price Index	-0.0007***	0.0001***	0.0008***	0.0002
	(0.0002)	(0.0000)	(0.0001)	(0.0002)
Constant	-5.0107***	1.2979***	4.7541***	1.0413
	(1.6347)	(0.4031)	(1.3473)	(1.8839)
Observations	20,476	20,476	20,476	20,476
R-squared	0.8814	0.8415	0.8919	0.9334
Time FE	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1) and are clustered at zipcode level. The analysis is conducted on a PSM matched sample.

Table 8: Heterogeneous Effects of Airbnb's Entry on Bankruptcy Exemption Policy across States

	(1) Mortgage Loans H	(2) Mortgage Loans L	(3) Auto Loans H	(4) Auto Loans L	(5) Bankcard Loans H	(6) Bankcard Loans L
Entry of Airbnb	-0.0309*	-0.0827***	-0.0228	-0.0852***	-0.00761	-0.0195
	(0.0187)	(0.0275)	(0.0185)	(0.0310)	(0.0118)	(0.0187)
High School or Higher	0.0300***	-0.00587	0.00141	-0.00611	-0.00625*	-0.000403
	(0.00499)	(0.00821)	(0.00539)	(0.00695)	(0.00367)	(0.00492)
No. of Households Log.	-0.823***	-0.837*	-0.0266	-0.423	0.425**	0.314
	(0.260)	(0.495)	(0.272)	(0.441)	(0.185)	(0.427)
Median Income	0.0104***	-0.000303	-0.00384*	-0.00424	0.000347	-0.00203
	(0.00219)	(0.00328)	(0.00233)	(0.00388)	(0.00159)	(0.00244)
Poverty Rate	0.0163***	0.0124**	-0.00393	0.000953	-0.000766	0.00414
	(0.00433)	(0.00626)	(0.00456)	(0.00584)	(0.00318)	(0.00410)
Unemployment Rate	0.0147***	-0.00984	0.0127**	0.00443	0.00543	-0.0000721
	(0.00446)	(0.00829)	(0.00552)	(0.00745)	(0.00341)	(0.00559)
Ratio of Second Mortgage	0.0188***	0.00691*	0.00865***	0.00649	0.00295*	-0.00229
	(0.00221)	(0.00376)	(0.00244)	(0.00436)	(0.00166)	(0.00335)
Housing Price Index	-0.00460***	-0.00350***	-0.00229***	-0.00312***	-0.000740***	-0.00114**
	(0.000452)	(0.00103)	(0.000428)	(0.000913)	(0.000266)	(0.000577)
Constant	10.33***	14.48**	3.366	9.074*	-1.019	-0.0161
	(3.335)	(6.224)	(3.528)	(5.475)	(2.372)	(5.329)
Observations	80,074	35,686	78,484	34,839	80,473	35,908
R-squared	0.954	0.954	0.940	0.935	0.971	0.969
Zipcode Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1) and are clustered at zipcode level. We estimate the effects of Airbnb's entry across different states and District of Columbia in U.S., based on their bankruptcy exemption policy. By investigating the homestead exemption values by law of different states and the District of Columbia, we summarize a sample of states of low homestead exemption values (lower than 20,000 or no exemption is granted) and high homestead exemption values (higher than 100,000 or allowed to keep all property regardless of values). We conduct analysis on the the propensity score matched sample. Within each sample, we differentiate the effects of Airbnb's entry by low homestead exemption and high homestead exemption values.

Table 9: Heterogeneous Effects of Airbnb's Regulation on Bankruptcy Exemption Policy across States

	(1) Mortgage Loan H	(2) Mortgage Loan L	(3) Auto Loan H	(4) Auto Loan L	(5) Bankcard Loan H	(6) Bankcard Loan L
Entry of Airbnb	-0.0200	-0.1071***	0.0015	0.0107**	0.0284	0.0273
	(0.0185)	(0.0211)	(0.0053)	(0.0043)	(0.0238)	(0.0239)
Entry of Airbnb × τ	0.0052***	0.0050***	-0.0002	-0.0006	-0.0055***	0.0003
	(0.0013)	(0.0015)	(0.0003)	(0.0005)	(0.0013)	(0.0017)
Regulation	0.0450***	-0.0082	-0.0023	0.0146***	-0.0150	0.0479***
	(0.0112)	(0.0100)	(0.0028)	(0.0042)	(0.0121)	(0.0124)
High School or Higher	0.0077**	0.0017	0.0040***	0.0017	0.0144***	0.0040
	(0.0032)	(0.0050)	(0.0009)	(0.0016)	(0.0025)	(0.0042)
No. of Households Log	0.3052	0.0477	-0.1162***	0.0362	-0.2157	-0.2556
	(0.2035)	(0.3369)	(0.0414)	(0.1552)	(0.1670)	(0.2889)
Median Income	0.0000***	-0.0000***	-0.0000**	0.0000	0.0000	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Poverty Ratio	0.0016	0.0061	0.0012*	-0.0008	-0.0008	0.0049
	(0.0027)	(0.0037)	(0.0006)	(0.0013)	(0.0020)	(0.0032)
Unemployment Rate	0.0375***	0.0096	0.0008	0.0028	-0.0058*	-0.0124**
	(0.0058)	(0.0071)	(0.0009)	(0.0026)	(0.0034)	(0.0060)
Ratio of Second Mortgage	0.0140***	0.0035	0.0024***	0.0016	0.0063***	0.0021
	(0.0027)	(0.0029)	(0.0006)	(0.0011)	(0.0024)	(0.0020)
Housing Price Index	-0.0014***	-0.0006	0.0002***	0.0001	0.0012***	0.0007
	(0.0003)	(0.0005)	(0.0000)	(0.0001)	(0.0002)	(0.0004)
Constant	-4.6477*	-0.5102	1.2120**	-0.5931	1.9457	3.4557
	(2.7713)	(4.4299)	(0.5610)	(2.1375)	(2.2563)	(3.7313)
Observations	8,392	3,332	8,392	3,332	8,392	3,332
R-squared	0.8657	0.9017	0.8358	0.8567	0.8988	0.8908
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1) and are clustered at zipcode level. We conduct analysis on the the propensity score matched sample.

Table 10: Parallel Trends Test – Entry

	(1) Mortgage Loans	(2) Auto Loans	(3) Bankcard Loans
Airbnb Entry Lag 6	0.000676	0.0147	0.000705
	(0.00774)	(0.00911)	(0.00536)
Airbnb Entry Lag 5	0.000736	0.0147	0.00217
	(0.00774)	(0.00952)	(0.00530)
Airbnb Entry Lag 4	0.00291	0.0145	-0.00130
	(0.00752)	(0.00984)	(0.00538)
Airbnb Entry Lag 3	0.00188	0.0148	-0.00169
	(0.00783)	(0.00990)	(0.00526)
Airbnb Entry Lag 2	-0.000904	0.0149	-0.00702
	(0.00784)	(0.00965)	(0.00534)
Airbnb Entry Lag 1	-0.00849	0.0100	-0.00831
	(0.00819)	(0.00973)	(0.00531)
Airbnb Entry Lead 0 Omitted	–	–	–
	–	–	–
Airbnb Entry Lead 1	-0.0144*	0.00243	-0.00717
	(0.00808)	(0.00971)	(0.00574)
Airbnb Entry Lead 2	-0.0147*	-0.00469	-0.00528
	(0.00819)	(0.00997)	(0.00564)
Airbnb Entry Lead 3	-0.0150*	-0.00265	0.0000903
	(0.00789)	(0.00960)	(0.00548)
Airbnb Entry Lead 4	-0.0192**	-0.00328	-0.00105
	(0.00810)	(0.00954)	(0.00551)
Airbnb Entry Lead 5	-0.0193**	-0.00105	-0.00106
	(0.00816)	(0.00926)	(0.00534)
Airbnb Entry Lead 6	-0.0145*	-0.00289	0.000371
	(0.00767)	(0.00911)	(0.00522)
High School or Higher	0.0166***	0.000678	-0.00103
	(0.00349)	(0.00346)	(0.00274)
No. of Households Log.	-1.198***	-0.441**	0.127
	(0.183)	(0.177)	(0.1268)
Median Income	-0.00614***	-0.00609***	-0.00405***
	(0.00135)	(0.00145)	(0.000876)
Poverty Rate	0.00624**	-0.00698***	-0.00512***
	(0.00262)	(0.00267)	(0.00191)
Unemployment Rate	0.0254***	0.0113***	0.00736***
	(0.00311)	(0.00320)	(0.00224)
Ratio of Second Mortgage	0.0181***	0.0105***	0.00638***
	(0.00156)	(0.00168)	(0.00122)
Housing Price Index	-0.00729***	-0.00221***	-0.00125***
	(0.000262)	(0.000236)	(0.000153)
Constant	18.04***	8.939***	2.445
	(2.382)	(2.314)	(1.659)
Observations	194,128	190,289	195,004
R-squared	0.954	0.938	0.972
Zipcode Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1), and are clustered at each zipcode level.

Table 11: Parallel Trends Test – Regulation

	(1) Mortgage Loans	(2) Auto Loans	(3) Bankcard Loans
Regulation Lag 6	-0.0022	0.0024	0.0103*
	(0.0039)	(0.0016)	(0.0060)
Regulation Lag 5	-0.0031	-0.0014	-0.0118**
	(0.0047)	(0.0018)	(0.0049)
Regulation Lag 4	-0.0027	0.0021	-0.0146**
	(0.0045)	(0.0018)	(0.0062)
Regulation Lag 3	0.0070	0.0049***	-0.0037
	(0.0044)	(0.0018)	(0.0062)
Regulation Lag 2	0.0108**	0.0031**	0.0031
	(0.0042)	(0.0016)	(0.0050)
Regulation Lag 1 Omitted	–	–	–
	–	–	–
Regulation Lead 0	0.0092	0.0000	0.0018
	(0.0070)	(0.0015)	(0.0072)
Regulation Lead 1	0.0139***	0.0058***	-0.0028
	(0.0047)	(0.0015)	(0.0073)
Regulation Lead 2	0.0199***	0.0080***	0.0024
	(0.0048)	(0.0018)	(0.0062)
Regulation Lead 3	0.0162***	0.0060***	-0.0124**
	(0.0054)	(0.0016)	(0.0054)
Regulation Lead 4	0.0258***	0.0059***	-0.0273***
	(0.0054)	(0.0014)	(0.0061)
Airbnb Entry $\times$ τ	-0.0023	0.0031***	0.0079
	(0.0063)	(0.0012)	(0.0067)
High School or Higher	0.0009	-0.0010	0.0093**
	(0.0049)	(0.0008)	(0.0037)
No. of Households Log	0.9388***	-0.1194***	-0.9433***
	(0.1930)	(0.0338)	(0.1650)
Median Income	-0.0000***	-0.0000*	0.0000*
	(0.0000)	(0.0000)	(0.0000)
Poverty Rate	0.0014	-0.0007	-0.0054***
	(0.0021)	(0.0005)	(0.0020)
Unemployment Rate	0.0097***	-0.0010	-0.0009
	(0.0039)	(0.0010)	(0.0045)
Ratio of Second Mortgage	-0.0038*	-0.0001	0.0030
	(0.0021)	(0.0005)	(0.0020)
Housing Price Index	-0.0003	0.0000	0.0000
	(0.0002)	(0.0000)	(0.0002)
Constant	-12.2021***	1.7197***	12.1990***
	(2.6439)	(0.4694)	(2.2321)
Observations	6,662	6,662	6,662
R-squared	0.9137	0.9111	0.9209
Zipcode Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1), and are clustered at each zipcode level.

Table 12: Panel VAR Model with Exogenous Entry

	(1) Mortgage Loan	(2) Auto Loan	(3) Bankcard Loan
Mortgage Loan Lag 1	0.8896***	0.0249	0.0436**
	(0.0160)	(0.0158)	(0.0204)
Mortgage Loan Lag 2	0.0290***	-0.0042	0.0010
	(0.0088)	(0.0086)	(0.0103)
Auto Loan Lag 1	-0.0001	0.8887***	0.0381*
	(0.0166)	(0.0156)	(0.0207)
Auto Loan Lag 2	-0.0142*	0.0707***	0.0206**
	(0.0078)	(0.0082)	(0.0095)
Bankcard Loan Lag 1	-0.0075	0.0886***	1.0152***
	(0.0308)	(0.0282)	(0.0393)
Bankcard Loan Lag 2	0.0015	0.0060	0.0489***
	(0.0097)	(0.0099)	(0.0113)
Entry of Airbnb	-0.0351***	0.0103	0.0232
	(0.0126)	(0.0121)	(0.0174)
High School or Higher	0.0376*	-0.0060	-0.0086
	(0.0223)	(0.0210)	(0.0319)
No. of Households Log	-0.4539	1.2994**	1.9644**
	(0.6296)	(0.5815)	(0.8101)
Median Income	0.0011	-0.0008	-0.0017
	(0.0012)	(0.0012)	(0.0017)
Poverty Ratio	0.0024	0.0110	0.0213
	(0.0112)	(0.0101)	(0.0149)
Unemployment Rate	0.0044	0.0002	0.0026
	(0.0037)	(0.0033)	(0.0048)
Ratio of Second Mortgage	0.0061**	0.0002	-0.0023
	(0.0026)	(0.0025)	(0.0033)
Housing Price Index	-0.0016***	0.0009	0.0018**
	(0.0006)	(0.0006)	(0.0008)
Observations	134,288	134,288	134,288

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1), and are clustered at each zipcode level.

Table 13: Panel VAR Model with Endogenous Entry

	(1) Mortgage Loan	(2) Auto Loan	(3) Bankcard Loan	(4) Airbnb's Entry
Mortgage Loan Lag 1	0.8902***	0.0246	0.0431**	-0.0097
	(0.0157)	(0.0155)	(0.0199)	(0.0089)
Mortgage Loan Lag 2	0.0291***	-0.0043	0.0009	0.0019
	(0.0087)	(0.0087)	(0.0101)	(0.0051)
Auto Loan Lag 1	0.0005	0.8885***	0.0377*	-0.0186**
	(0.0166)	(0.0155)	(0.0205)	((0.0088))
Auto Loan Lag 2	-0.0140*	0.0706***	0.0205**	-0.0058
	(0.0078)	(0.0082)	(0.0094)	(0.0043)
Bankcard Loan Lag 1	-0.0064	0.0884***	1.0145***	-0.0402**
	(0.0307)	(0.0281)	(0.0391)	(0.0166)
Bankcard Loan Lag 2	0.0017	0.0060	0.0488***	-0.0090*
	(0.0097)	(0.0099)	(0.0112)	(0.0053)
Airbnb's Entry Lag 1	-0.036***	0.0084	0.0223	0.9868***
	(0.0118)	(0.0118)	(0.0160)	(0.0073)
Airbnb's Entry Lag 2	0.0010	0.0021	0.0011	-0.0014
	(0.0029)	(0.0041)	(0.0029)	(0.0009)
High School or Higher	0.0378*	-0.0059	-0.0086	-0.0197
	(0.0222)	(0.0209)	(0.0317)	(0.0136)
No. of Households Log	-0.4366	1.2927**	1.9517**	-0.4740
	(0.6264)	(0.5788)	(0.8049)	(0.3413)
Median Income	0.0011	-0.0008	-0.0017	-0.0011
	(0.0012)	(0.0012)	(0.0017)	(0.0007)
Poverty Ratio	0.0027	0.0109	0.0211	-0.0118*
	(0.0112)	(0.0101)	(0.0148)	(0.0063)
Unemployment Rate	0.0044	0.0002	0.0026	-0.0015
	(0.0037)	(0.0033)	(0.0048)	(0.0021)
Ratio of Second Mortgage	0.0060**	0.0002	-0.0022	-0.0007
	(0.0026)	(0.0025)	(0.0032)	(0.0014)
Housing Price Index	-0.0016***	0.0009	0.0018	-0.0001
	(0.0006)	(0.0006)	(0.0008)	(0.0003)
Observations	134,288	134,288	134,288	134,288

Notes: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1), and are clustered at each zipcode level.

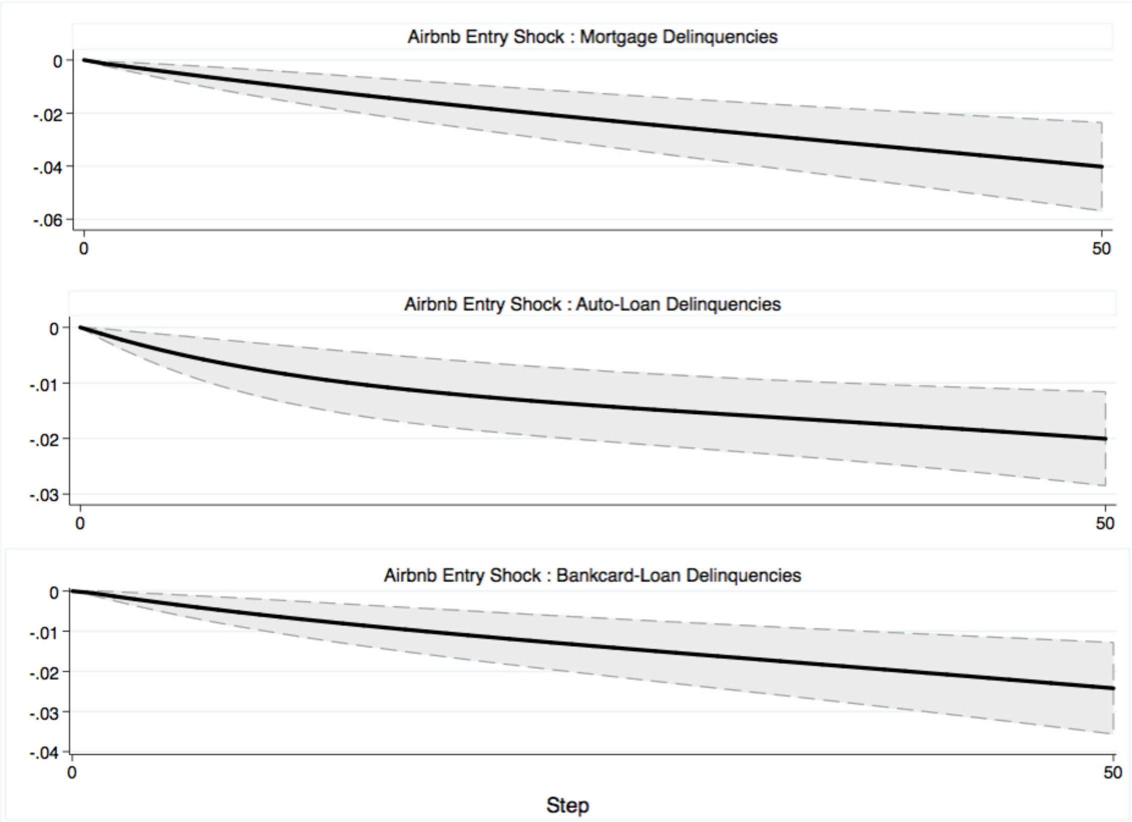

Figure 1: Shock of Airbnb's Entry on Mortgage Loan, Auto Loan and Bankcard Loan Delinquencies

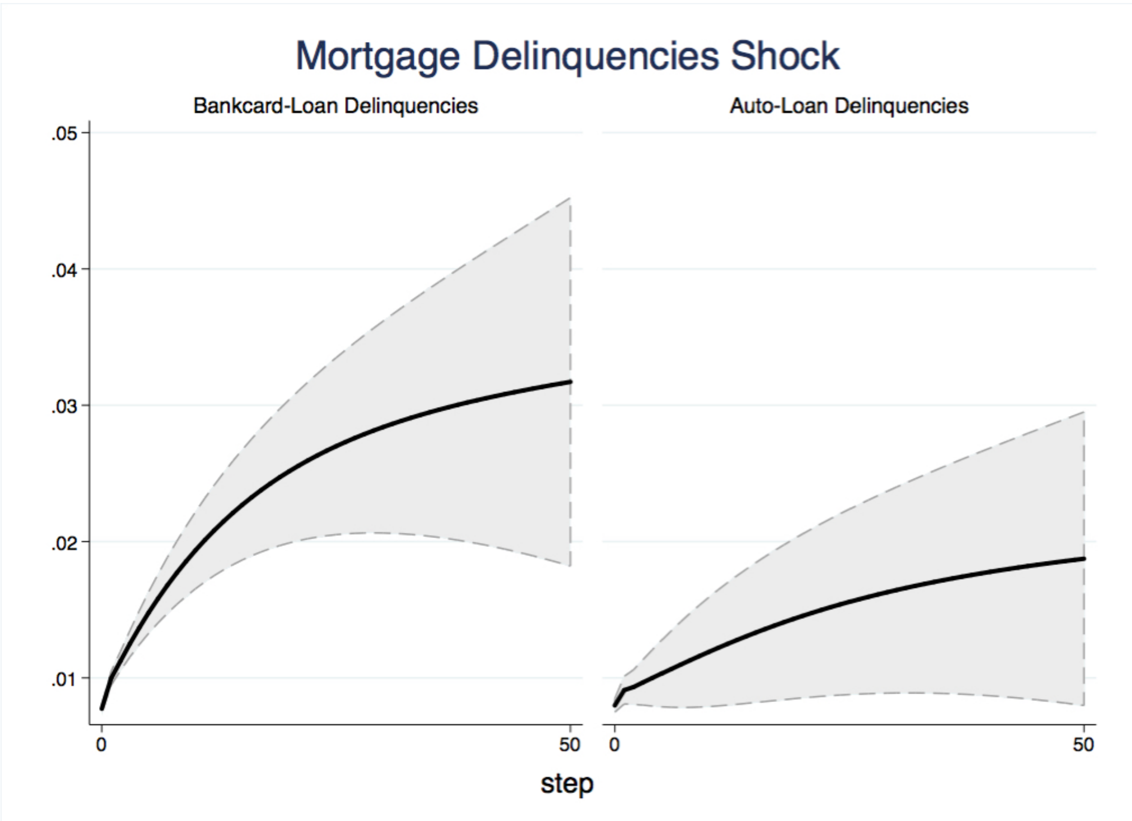

Figure 2: Shock of Mortgage Loan Delinquencies on Bankcard Loan and Auto Loan Delinquencies

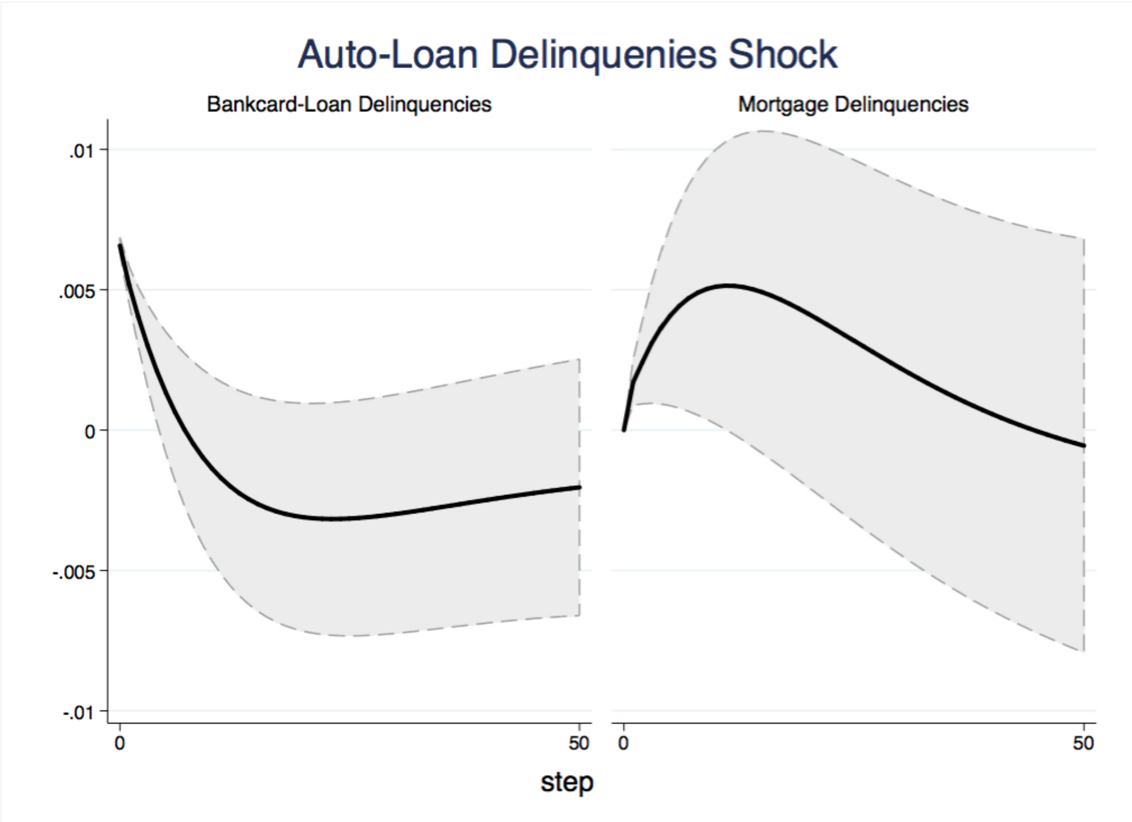

Figure 3: Shock of Auto Loan Delinquencies on Mortgage Loan and Bankcard Loan Delinquencies

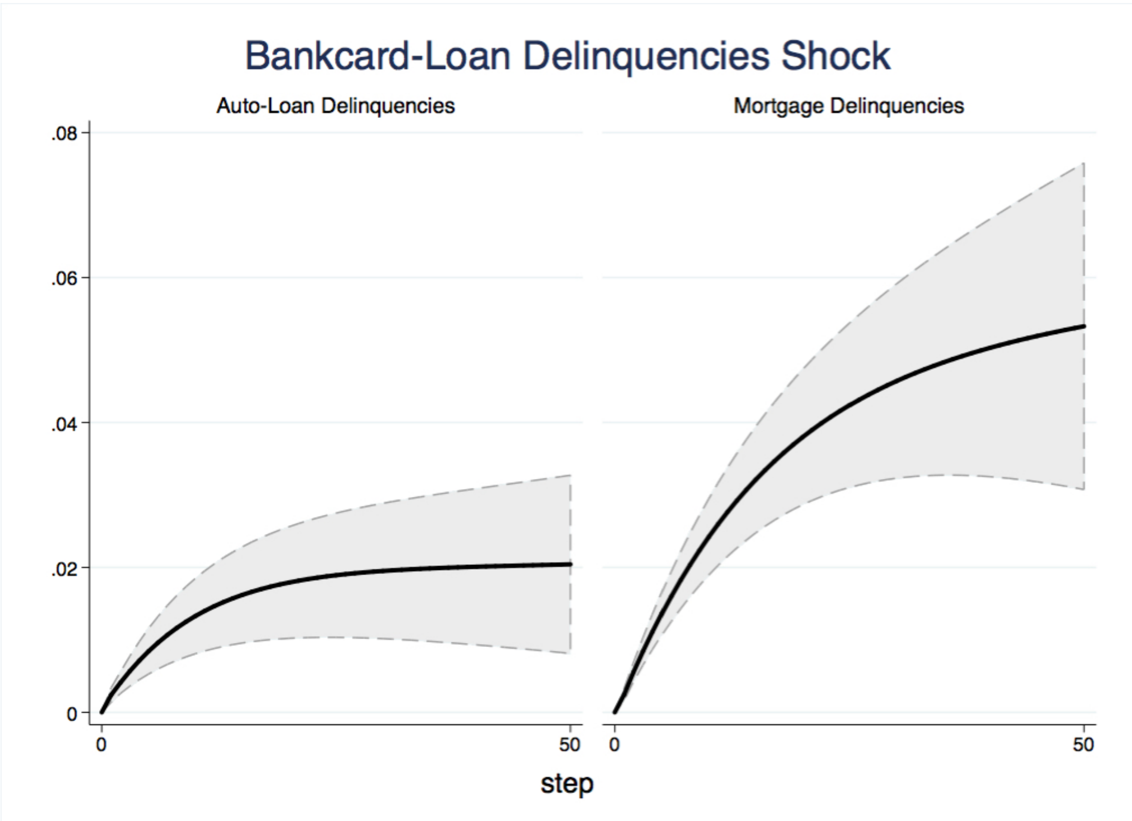

Figure 4: Shock of Bankcard Loan Delinquencies on Auto Loan and Mortgage Loan Delinquencies