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Credit Constraints and Fraud Victimization

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Abstract

Using a novel, nationally representative data set on fraud victimization, this paper examines the impact of credit constraints on fraud victimization and potential underlying mechanisms in Chinese urban areas. After controlling for other household characteristics and regional fixed effects, households facing credit constraints are associated with 2.3 percentage points higher probability of becoming fraud victims, and have 20.4 percent higher subsequent economic losses from fraud when they are approached. The results are robust when dealing with the endogeneity of facing credit constraints and when addressing potential sample selection bias. Further analyses show that the personal discount rate (impatience) and the need for social network expansion are critical pathways via which credit constraints affect fraud victimization. The findings suggest that improving financial development is an effective way to reduce fraud victimization.

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Credit Constraints and Fraud Victimization: Evidence from a Representative Chinese Household Survey[1]

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[1] The paper represents the views of the authors and do not implicate the World Bank and its membership countries.

1. Introduction

Fraud is an ancient crime of deception that aims to obtain money or other benefits from people. In Dante's description of inferno in the Divine Comedy, fraud is considered as one of the worse sins--people who committed fraud would endure punishment at the *Bolgia* eight of *Malebolge* (eighth circle of hell).

Fraud victimization has profound economic and social implications. With the widespread leakage of private information, especially via the internet, and the ever-evolving fraud schemes, people frequently encounter fraud schemes, yet find it increasingly difficult to avoid victimization. Millions of people suffer from fraud victimization with enormous economic losses every year. As much as 11 percent of Americans (about 25.6 million) in 2011 and 4 percent of Australians in 2012 were victims of fraud schemes (Anderson, 2013; Jorna and Hutchings, 2013). A Federal Trade Commission (FTC) survey reveals that the individual/household level economic losses due to fraud victimization ranged from $40 to $40,000 in 2005 (Reisig and Holtfreter, 2007). In 2011 alone, 2.7 percent of Americans (i.e., 6.4 million people) paid at least $1.9 billion in total to fraudsters in various forms (Anderson, 2013), and the direct monetary costs incurred by victimization could reach $50 billion (Brenner et al., 2020).

The issue is of greater importance in developing countries. In China, for instance, fraud incidents have grown at an annual rate of 20 to 30 percent in the past decade.[2] According to a report by the Government of China, nearly half of internet users encountered fraud schemes in 2018, and 28 percent of them suffered economic losses.[3] Based on judicial data, fraud is one of the most frequent crimes, accounting for 32 percent of cybercrime that involves 46,000 fraudsters.[4]

The previous literature, mostly in criminology, has examined the behavioral patterns of fraudsters (Levi, 2008). Behind the commonly encountered fraud phone calls and emails are well-trained fraudsters in criminal organizations with sophisticated technologies.[5]

[2] https://www.tisi.org/4714

[3] http://www.gov.cn/xinwen/2019-09/17/content_5430594.htm

[4] https://www.secrss.com/articles/15226

[5] Levi (2008) classifies the common fraud schemes into 6 categories and 34 items according to the characteristics of fraud victims (such as financial-services-related, non-financial-services-related, individual-level, national-level, and so on). Based on the intermediation and formation of schemes, the Federal Bureau of Investigation (FBI) has categorized common fraud into 24 different items, including common schemes such as credit card fraud, investment fraud, Nigerian letter fraud (also called 419), Ponzi schemes, and

Those organizations are armed with details about potential victims and "scripts" instructing fraudsters on how to persuade potential victims to buy their stories and make money transfers (Levi, 2008). However, it remains unclear why fraud victims are victimized. In this paper, we investigate fraud victimization from the perspective of household financial conditions. Specifically, how and why do household credit constraints affect fraud victimization when facing fraud schemes?

Though our data have both urban and rural households, our investigation of the relationship between credit access and fraud victimization relies on the urban sample for several reasons. First, we have a credible identification strategy for the effects of credit constraints only for urban households, with details to be explained later. Second, previous research has shown that rural and urban access to credit differ greatly. Rural residents have much less access to bank finance and depend to a much greater extent on informal finance (Cull et al., 2019). Finally, rural and urban residents also differ greatly in their fraud victimization behavior, with rural residents living in more sparsely-populated areas, facing less social interaction, and using the internet less (i.e., a major source of fraud). We thus focus only on urban residents in this paper.[6]

Using the urban sample of a novel nationally-representative data set on fraud victimization and household finance, we find that households facing credit constraints is a key determinant of fraud victimization. The baseline regression results show that being credit constrained is associated with 2.3 percentage points increase in the probability of becoming a victim, and 20.4 percent increase in the total amount of subsequent economic losses for those being approached, after controlling for other household characteristics and regional fixed effects. To deal with potential omitted variable bias and reverse causality issues, we employ the instrumental variables (IV) approach where the exposure to a nation-wide property privatization reform, which happened only in the urban areas, and the local

telemarketing and other forms (for more detail, see https://www.fbi.gov/scams-and-safety/common-fraud-schemes). Those schemes differ from each other in many ways, from targeting subjects to operating tools. For example, gambling scams take advantage of people's willingness to win gambles. Fraudsters send email to potential victims and tell them that they need to pay a small amount of fee in advance to guarantee winning an imaginary big prize/lottery/rewards. Investment frauds encourage people to participate in fake and rare investment opportunities with absurd returns. Bogus products and services provide potential victims useless health care products, psychic services, fake career opportunities, and so on (Button et al., 2009).

[6] At this stage, we have much less understanding of fraud victimization in rural areas, as will be implied in the literature survey. This topic is thus left for future research.

bank density are used as exogenous shifters of credit constraints. In the 1990s, China implemented an unexpected nation-wide housing privatization reform that allowed urban residents to purchase and privately own the state-owned housing in which they lived. Since the purchasing price was subsidized and lower than the market price, and the private housing can be used as collateral to obtain loans from financial institutions, privatized housing led to an exogenous increase in household wealth and loosened household financial constraints (Wang, 2012; Li and Wu, 2014). Meanwhile, local bank density is a good indicator for access to formal bank finance. Living in an area with higher density of bank branches can foster access to credit and decrease the likelihood of credit constraints (Rajan and Ramcharan, 2011; Rossi and Trucchi, 2016). The IV estimation results confirm that credit constraints lead to higher probability of fraud victimization and higher subsequent economic losses.

We also consider the selectivity of fraud victimization. Fraud victimization involves two steps: being approached, and subsequently being victimized. If being approached is not random, and the probability of being approached and of being victimized are jointly determined by unobservables, selection bias is a concern. To address this issue, we implement the Heckman selection model, where we first model the probability of being approached and then, conditional on being approached, we estimate the models of the main outcomes (probability of victimization and subsequent economic losses). Since individuals with more frequent online shopping face a higher risk of exposure to fraud schemes (Holtfreter et al., 2008; Reisig and Holtfreter, 2013), we exploit the E-commerce coverage at the community level as an exogenous source of variation to determine the probability of being approached by fraudsters. Our main findings remain robust.

We further rule out the confounding effect of information acquisition and financial literacy on fraud outcomes. Since credit-constrained households may fail to acquire anti-fraud information released by banks or other credit institutions, a natural concern is that it may be the anti-fraud information acquisition, rather than facing credit constraints, that causes fraud victimization. Furthermore, a higher level of financial literacy helps people better understand financial products and make better financial decisions and distinguish legitimate investment projects from fraud schemes. The estimated impact of credit constraints on fraud victimization may thus be confounded by financial literacy. To address these concerns, we add indicators of information acquisition and financial literacy in the main model. Our main results remain robust, indicating that neither information acquisition nor financial literacy drives the link between credit constraints and fraud victimization.

Further analyses on potential mechanisms suggest that the personal discount rate (impatience) and the need to expand the social network are important pathways through which credit constraints affect fraud victimization. Borrowing constraints can shape people's preferences on current versus future consumption (Harrison et al., 2002; Ventura, 2003; Nakata and Sawada, 2015). Credit constraints may lead to a higher discount rate over the future, and thus make people more prone to believe well-disguised fraud schemes that promise an egregious return within a short period. In addition, to obtain social collateral, households with severe credit constraints would engage in activities to expand their social networks; more social interaction itself, along with the associated behavior changes such as emphasis on cooperative behavior, could make them more susceptible to become victims.

We contribute to the literature in several ways. First, we propose a new perspective to understand fraud victimization. To the best of our knowledge, while there is an economic literature on credit constraints and crime (Garmaise and Maskowitz, 2006; Cortés et al., 2016; Avenancio-León, 2019); Palmer et al., 2019), this is the first paper using nationally representative data on fraud to examine the impact of credit constraints on fraud victimization. Thanks to the richness of our data, we look at both people being approached for fraud and victimization. Second, we explore the mechanisms through which credit constraints affect fraud victimization. Third, we assess the effects of alternative policies to combat fraud (such as improving information acquisition and financial literacy) and find that improving financial access is more effective in reducing fraud victimization. Finally, we contribute to the literature on the impact of credit constraints. It is well established in the literature that credit constraints can shape household behaviors such as consumption (Garcia et al., 1997; Jappelli et al., 1998), entrepreneurship (Hurst and Lusardi, 2004), precautionary saving (Lee and Sawada, 2010), and labor supply (Rossi and Trucchi, 2016). We find that credit constraints have an additional consequence: fraud victimization.

The rest of this paper is organized as follows. Section 2 introduces the institutional background, reviews the previous literature, and presents the conceptual framework. Section 3 describes the data. Section 4 describes the methods. Section 5 presents the empirical results. Sections 6 and 7 further discuss selection bias and alternative interpretations. Section 8 discusses the mechanisms. Section 9 concludes.

2. Background and Hypotheses

We first introduce the institutional background on housing privatization in urban China, which would form the base upon which to identify the effect of credit constraints on fraud victimization. We then review the previous literature on fraud victimization. We lastly discuss our conceptual framework on why credit constraints affect fraud victimization.

2.1 Housing privatization

There was no housing market in the 1970s in China.[7] The housing provision then was based on the Socialist model with housing being treated as part of the welfare benefit (Chen and Gao, 1993). Most urban residents lived in state-owned shelters provided by the state or state-owned enterprises (Wang and Murie, 2000). To deal with housing supply shortage, distortion of residential mobility and employment, and limited property investment, the Chinese government initiated the market-oriented housing reform through housing privatization (Wang and Murie, 1996; Wang, 2011).

After piloting in several cities in a decade, in 1988 the Chinese government launched the housing reform nationwide. The State Council issued the *Implementation Plan for a Gradual Housing System Reform in Cities and Towns*, which aimed to create a housing market through privatization. Housing rent rose, and the housing fund was established. In addition, state-owned housing was allowed to be sold to sitting tenants, giving them an opportunity to own a private property (Wang and Murie, 2000; Huang and Clark, 2002). With the nationwide inflation and political events in late 1980s, the process of housing reform was slow. At the beginning of the 1990s, the central authorities required the implementation of housing reform in all cities. The housing reform was pushed forward forcefully, especially with the selling of state-owned housing to sitting tenants. At the end of 1993, the authorities suspended the housing reform because of the very low price at which the state-owned housing was transacted (Wang and Murie, 1996, 2000; Man, 2011).

In 1994, the Housing Reform Steering Group of the State Council issued *The Decision on Deepening the Urban Housing Reform.* The property privatization in China stepped into

[7] All our institutional background here concerns only urban residents.

a comprehensive stage. Privatization was implemented through a differentiated housing price mechanism. Middle- or low-income families were subsided to purchase the existing state-owned housing with a lower price that covered only the construction cost, tax and other fees, while high-income families were able to purchase/sell the full property of state-owned housing according to the market price (Wang and Murie, 2000; Wang, 2012; Liu and Xiong, 2018). Housing market was further formalized with price being set by the market. However, the state via the work-units still play an important role in housing distribution. Work units were responsible for granting housing subsidy, constructing and purchasing new housing projects, and selling (or renting) the state-owned shelters to employees (Logan et al., 1999; Huang and Clark, 2002; Ho and Kwong, 2002; Deng et al., 2014).

At the end of the 1990s, the authorities issued a document *On Further Deepening the Reform of Urban Housing System to Speed up the Construction of Housing,* which marked the milestone of housing privatization and commercialization reform (Li and Wu, 2014; Lee, 2000). This reform intended to *suspend* the distribution of public housing through the state/work-units and introduce a cash subsidy for housing (Wang and Murie, 2000). The authorities wished to build a system in which a small proportion of residents would purchase commodity housing through the market, and the rest could get access to housing through affordable housing programs. However, with rising income and rapid rural-to-urban migration, the demand for commodity housing skyrocketed, rendering infeasible the supply of affordable housing. As a result, the role of commodity housing and affordable housing reversed, and commodity housing was treated as a pillar of the economic growth.

The housing privatization has greatly stimulated property investment (Cao et al., 2018). The proportion of real estate investment accounted for 15 percent of China's GDP in 2013 (Chen et al., 2017). The housing market has experienced a great appreciation, with the housing price index in 2017 being 4.5 times higher than that in 2003, and the average housing price in major cities appreciating more than 400 percent from 2003 to 2017 (Liu and Xiong, 2018).

For residents, property privatization significantly reduced their financial constraints (Wang, 2011, 2012). Many state-owned-enterprises (SOEs) workers became significantly wealthier because of the substantial gap between market price and subsidized price (Wu et al., 2012; Wang, 2012).[8] For the households that experienced the housing privatization reform, moreover, they could capitalize on the value of their property by selling or using it as collateral for loans from banks.

2.2 Previous literature on fraud victimization

Previous studies on fraud victimization are mostly in criminology, mainly focusing on the demographic and psychological factors of the victims. Despite its potential policy significance, the role of households' financial condition is under-explored.

On being approached for fraud, earlier studies in criminology suggest that fraudsters choose targets randomly. Demographic characteristics such as age and education that are commonly used to predict individual victimization have no power in explaining fraud approaching (Holtfreter et al., 2008). But recent studies suggest that fraud approaching is likely related to individual psychological characteristics. Fraudsters prefer to target individuals that exhibit obvious psychological issues (such as anger, greed, anxiety, and a lack of self-control), because they are more likely to be socially isolated and cognitively impaired (Langenderfer and Shimp, 2001; Shadel and Pak, 2007; Van Wilsem, 2013). In addition, for certain types of fraud schemes, fraudsters would track consumers' detailed purchasing records, and exclude those who are cautious and exhibit no interest in the advertised products (Shover et al., 2004). People with frequent online shopping experiences are more likely targeted (Holtfreter et al., 2008; Reisig and Holtfreter, 2013).

In contrast to the criminology finding that demographic characteristics do not matter in approaching households, studies in other fields document that demographic and psychological factors (such as age, education, household income, trustiness, online purchasing behavior, degree of self-control, and social status) are highly correlated with fraud victimization (Marlowe and Atiles, 2005; Anderson, 2007; Alves and Wilson, 2008; Ross et al., 2014; Lichtenberg et al., 2016). Due to decreased cognitive ability, abundant free time and loneliness, the older population are more vulnerable to fraud schemes (Ross et al., 2014; Alves and Wilson, 2008). Supportive evidence is found in different countries and periods (Temple, 2007; Reisig and Holtfreter, 2013; Lichtenberg et al., 2016).[9]

[8] The average difference between the market value and the purchasing value was estimated at 24,462 RMB (about $3,545) (Wang, 2012).

[9] Some question the effect of old age on fraud victimization. Titus and Gover (2001) point out that the older population are predicted to have a higher probability of victimization just because they are more willing to

Furthermore, self-control is another factor that predicts fraud victimization (Schreck, 1999; Schreck et al., 2006; Reisig and Holtfreter, 2013). Individuals with lower levels of self-control are more likely to become fraud victims because they are more likely to be short-sighted, and they find it hard to resist the temptation of promised immediate return with little inputs (Holtfreter et al., 2008; Van Wilsem, 2013).

However, most of the aforementioned results are correlational evidence, and are based on selected samples consisting of either limited number of victims or telephone-interviewed older population. Alves and Wilson (2008) study the vulnerability of the elderly by using a sample consisting of 28 fraud victims. Titus and Gover (2001) and Mears et al. (2016) employ a telephone-survey data set to estimate the incidence and prevalence of fraud victimization. About 2,000 telephone respondents aged 60 and above form the sample used in Mears et al. (2016). Sample selection and insufficient sample size issues make the findings less convincing.

Several papers have examined the impact of credit accessibility on *crime* from the perspective of criminal offenders. Garmaise and Moskowitz (2006) find that local bank merger induces poorer credit access and results in a large increase in crime. Cortés et al. (2016) find that cash grabbing crimes increase disproportionally after the crashing down of Ponzi schemes in 2008 in Colombia, and the effect is driven by limited access to credit. Aneja and Avenancio-León (2019) document that when there is a lack of access to credit, the deterring effect of incarceration on crime is smaller, and thus indirectly show credit constraints induce criminal behaviors. Palmer et al. (2019) find that financial assistance, on the other hand, can reduce criminal behavior. The total arrests in Chicago fell 1-2 years after temporary financial assistance to eligible individuals and households. This is likely due to greater housing stability associated with financial assistance. While this literature links credit constraints to crime, it does not address the relationship between credit constraints and financial fraud in particular.

The impact of credit constraints on households is well studied in the literature. Failure to borrow desired amounts of money may affect household behaviors. Zeldes (1989) shows that borrowing constraints lead to a violation of the Euler equation, which explains why household consumption would not imply Keynesian behavior empirically as predicted by

report their fraud experiences than others.

the permanent income hypothesis. Jappelli and Pagano (1994) find that credit constraints induce higher household saving rates, thus the positive effect of capital accumulation on growth rate is strengthened under the framework of an endogenous growth model. Jappelli et al. (1998) offer evidence that being credit constrained explains excess sensitivity of household consumption. The response of household members to restrictions in the credit market has expanded to many fields, such as portfolio choice (Guiso et al., 1996), entrepreneurship (Hurst and Lusardi, 2004), labor supply (Rossi and Trucchi, 2016), and saving (Lee and Sawada, 2010; Coeurdacier et al., 2015).

2.3 Conceptual framework

Credit constraints may make people more prone to fraud victimization via several channels. First, credit constraints can influence the personal discount rate (impatience), which in turn affects risk of fraud victimization. The discount rate refers to the intertemporal rate of substitution of different levels of consumption in the present and future (Pender, 1996). Less patient, people with a higher discount rate value the present more (Courtemanche et al., 2015). Previous studies show that households with credit constraints have higher discount rates. Warner and Pleeter (2001) find that individuals who face severe discrimination in the credit market would encounter higher market borrowing rates, which indicates a stronger preference for current versus future consumption and higher discount rates. This finding is also verified in other studies (Lawrance, 1991; Harrison et al., 2002; Ventura, 2003; Nakata and Sawada, 2015; Dean and Sautmann, 2020). In our scenario, households with credit constraints have unmet credit needs, which might make them more tempted to make a quick buck, and to be prone to well-disguised fraud schemes that promise high return within a short period.

Second, as people's social networks are of critical importance for access to informal borrowing, households restricted by the formal credit market may need to expand their social network to obtain credit from informal credit markets (Karlan, 2007; Karlan et al., 2009; Shoji et al., 2012; Cull et al., 2019). Additionally, experimental evidence shows that social networks can promote cooperation (Rand et al., 2011, 2014). Individuals with the need for social network expansion exhibit a higher level of cooperation than others. Therefore, to access informal credit, credit-constrained households need to expand their social network, which in turn promotes cooperative behavior, and makes them more likely to behave in accordance with fraudsters' scripts, and become victims of specific fraud schemes. Furthermore, the need for social network expansion also increases the amount of social interactions of credit-constrained people, which would increase the probability of encountering fraudsters.

Based on the analysis above, we propose our hypothesis. Households subject to credit constraints from formal credit institutions are more likely to suffer from fraud victimization. Credit constraints make people less patient and more susceptible to fraud schemes disguised with high returns in short periods. Credit constraints increase the needs of credit-constrained people for social network expansion, which in turn may increase their amount of social interactions and therefore the probability of encountering fraud, in addition to inducing them to behave more cooperatively to disguised fraud schemes, both of which increase the chance of fraud victimization.

3. Data

We rely on data from the Chinese Household Finance Survey (CHFS), conducted by the Survey and Research Center for China Household Finance at the Southwestern University of Finance and Economics. This survey was started from 2011 with a sample of 8,438 households covering 25 provinces in both urban and rural China. The CHFS sample size is enlarged every other year with a new wave of the survey. The most recent wave was conducted in 2019 with 40,000 households. We use wave 3 (CHFS-III) in 2015 because this is the only wave with nationally representative information on fraud victimization.

CHFS adopts a three-level (county, community and residents) stratified random sampling method. In CHFS-III, firstly 350 counties were randomly selected nationwide, then four communities within each county were randomly chosen, and finally, 25-50 (20) households in each community in urban (rural) areas from each community were randomly selected. The final sample consists of 37,000 households in 1,394 communities in 350 counties, which are located in 29 provinces.

There are several major advantages of using CHFS-III for this research. First, apart from information on demographics, CHFS contains a wide range of information on income/expenditure, financial assets, real estate, asset structure, among others. Second, it has details on household financing behavior and historical debt. Third, the 2015 survey additionally included a module on fraud victimization. This is perhaps the first nationally representative survey on fraud victimization. By utilizing nationally representative data on fraud victimization and household financial circumstances, we can better understand the nationwide patterns of fraud victimization and make more representative inferences about the impact of credit constraints on fraud victimization.

The patterns of fraud approaching are in Table 1. In CHFS-III, each household head is asked whether the family members were approached by fraudsters last year, and if so, the intermedium through which the fraudsters approached. If a household was indeed approached by fraudsters last year, the household is considered as a fraud-approached household. Perhaps alarmingly, 67.4 percent of urban Chinese households were approached by fraudsters through various intermedium.[10] In the past decades, urban areas in China have expanded vastly with massive population inflow, among which are many fraudsters seeking more "opportunities." The denser neighborhoods and the lifestyle in urban areas also involve more social interactions and easier leakage of private information. Since private information protection and fraudster arresting are costly, local provision of public safety services against fraud approaching is far from sufficient.

We classify the intermedium through which urban households were approached into telephone, texting (i.e., SMS, mail, and e-mail), and face-to-face contacts. Telephone is the most frequently used intermedium: 65.1 percent of urban households have been contacted by fraudsters over the telephone. While both texting and face-to-face contacts are less popular, texting is used more frequently than face-to-face contacts (14.1 percent vs. 8 percent).

Table 2 reports the differences in the probability of fraud victimization after being approached, using the subsample of approached urban households. We split the approached households into being credit constrained and not being credit constrained. Credit constraints happen when there are frictions in the supply of capital and individuals are unable to obtain sufficient loans from banks or other institutions (Hurst and Lusardi, 2004; Farre-Mensa and Ljungqvist, 2016). Following previous studies (Jappelli et al., 1998; Lee and Sawada, 2010; Rossi and Trucchi, 2016), we consider a household as being credit constrained if the household is unable to borrow money for any of the following reasons: (a) need loan, but being rejected by banks or other credit institutions; (b) unable to obtain

[10] The average ratio of being approached by fraudsters in the rural areas is 40.3 percent.

sufficient loans from banks or other credit institutions; (c) did not apply for loans because of no collateral, complex paperwork, outstanding loans, or likelihood of being rejected.

There are significant differences in the victimization ratio between those two types of urban households. Compared to non-credit-constrained urban households, the probability of becoming a fraud victim is 2.6 percentage points higher (significant at the 1 percent level) for the credit-constrained urban households, corresponding to a 49 percent ([0.079-0.053]/0.053) increase of the average victimization ratio for the non-credit-constrained urban households.

4. Methods

4.1 Baseline model

We employ the following model to estimate the relationship between credit constraints and fraud victimization:

$$Fraud\ victim_i = \alpha + \beta Credit\_cons_i + \gamma X_i + \theta_c + u_i \qquad (1)$$

Here $Fraud\ victim_i$ indicates the fraud victimization status of household i. Two outcome variables are used, $Victim_i$ and $lnVictim\_loss_i$. $Victim_i$ is a binary variable which equals to 1 if households experienced economic losses after being approached by fraudsters, and 0 otherwise. $lnVictim\_loss_i$ refers to the total amount of economic losses (in logarithm) due to being subject to fraud schemes. As defined earlier, $Credit\_cons_i$ is the key explanatory variable, indicating whether household i is credit constrained.

X_i is a vector of control variables, including household income, the household head's age and the age squared, gender, years of schooling, health status, and the living arrangement. Household income (in logarithm, *Lincome*) is also included and consists of labor income, income generated by operating enterprise/agriculture, investment income, transfer income from parents or relatives, and other income. As it is established in the literature that elder people are more likely to become victims of fraud (Alves and Wilson, 2008), we include the age (and its squared term) of the household head to control for the possible (nonlinear) relationship between age and fraud victimization. As a bad health condition may make people more susceptible to health-related fraud schemes (such as fake drug fraud, magic medicine fraud, and witch fraud), we include a binary variable to indicate household head having at least one chronic illnesses.[11] The previous research in criminology has shown that individuals who live alone are more likely to become crime victims (Shadel and Pak, 2007), so we include a dummy variable indicating the respondent living alone. We also include an indicator for male (*Male*) and years of schooling of the household head (*Schooling*) in the model. County fixed effects (θ_c) are controlled for. Standard errors are clustered at city level, and robust standard errors are used to correct for heteroskedasticity.

4.2 Instrumental variables model

It is possible that unobserved characteristics (such as personality and self-control) can affect both credit constraints and fraud victimization. Self-control can influence both criminal behavior and crime victimization (Holtfreter et al., 2010; Reisig and Holtfreter, 2013; Van Wilsem, 2013). Household members without good self-control may be easily lured by schemes (such as lottery winning, gambling opportunities, and interest-free loans) that increase the possibility of fraud victimization. Meanwhile, people with superb social and communication skills (or emotional intelligence) may be resourceful, making them less likely to be both credit-constrained and fraud victims. However, due to data constraint, we do not have measurements that can be used to proxy respondents' self-control,[12] or to construct panel data to eliminate other fixed traits.

To deal with potential endogeneity of the credit constraints indicator to infer causality, we employ the instrumental variables (IVs) strategy by exploiting the *property privatization reform* and *bank density* as exogenous sources of changes in household credit constraints. Using those two IVs can simultaneously capture both the demand and supply side effect on households' credit constraints. The key identifying assumption is that the property privatization reform and the bank density affect fraud victimization only through household credit constraints, conditional on the county fixed effects and the covariates.

To be specific, the first IV is a dummy variable indicating a household's exposure to the property privatization reform (PPR). Exposure to PPR might decrease the probability

[11] The chronic conditions include hypertension, hyperlipidemia, diabetes, stroke, heart disease, bronchitis, mental health issue, Alzheimer's disease, and Parkinson's disease.

[12] Tangney et al. (2004) develop the Brief Self-Control Scale to capture the important components of self-control, such as self-discipline, non-impulsive action, health habits, and so on. This measure has been widely used in the literature (Holtfreter et al., 2010; Reisig and Holtfreter, 2013; Van Wilsem, 2013).

of having credit constraints. As discussed earlier, before PPR, the majority of residents lived in state-owned housing, which could not be rented, sold, or used as collateral. The PPR allowed residents to own the formerly state-owned housing, and provided residents with opportunities to purchase the property right of the housing and fully capitalize their property.[13] As the purchasing price was subsidized to be substantially lower than the market price, privatized housing increased exogenously household wealth; moreover, it could be used as collateral to obtain loans from credit institutions. The timing and the implementation of the nationwide privatization reform are likely to be unrelated to unobserved determinants of fraud victimization. Based on our earlier description of the PPR timing, we choose 1994 as the year of nationwide implementation of PPR. Though there were some small-scale reforms before 1994, the focus and implementation of reform differed from city to city and the ratio of home ownership had been largely flat until 1993 (Wang, 2011). Following the previous literature (Wang, 2011, 2012), we consider households as being exposed to PPR if their members were working in state-owned enterprises or the government in 1994.

The second IV is the local bank density, which captures the accessibility to formal finance. Higher local density of bank or other credit institutions can foster the access to credit and decrease the likelihood of credit constraints (Rajan and Ramcharan, 2011; Rossi and Trucchi, 2016). The distribution of bank branches is exogenous to households and individuals, especially after controlling for county fixed effects. In China, the opening of a bank branch is strictly regulated--opening any bank branch requires obtaining a certificate issued by China Banking Regulatory Commission (CBRC). Every certificate records the information such as the opening date, address, and category of financial services. We collect the information on all the certificates of all bank branches in China and locate every bank branch. Since housing purchases are expensive and tend to rely on bank loans (Cull et al., 2019), we define our second instrumental variable as the total number of bank institutions within five kilometers of households' current residence (denoted as *Branch*). Since we have controlled for county fixed effects, we have held constant local characteristics such as the level of development, local culture, and the level of

[13] Strictly speaking, the land upon which the apartment is built still belongs to the state, but the residents have full control rights and transaction rights.

trustworthiness, and our local bank density IV is unlikely to reflect omitted local characteristics.

Table 3 presents the definitions and summary statistics of our key variables. Full sample descriptive statistics are presented in panel A. Overall, 3.8 percent of Chinese urban households were fraud victims in 2014, and the counterpart was 16 percent for Dutch citizens in 2007, 11 percent for U.S. residents in 2011, 8 percent for U.K. residents in 2006, 4 percent for Canada residents in 2006 or for Australian residents in 2012 (Anderson, 2013; Whitty and Buchanan, 2012; Jorna and Hutchings, 2013).[14] The average amount of economic losses associated with fraud victimization is 897 yuan ($126.5), and the maximum amount of losses is 3 million yuan ($423,131). Descriptive statistics on approached urban households are presented in panel B. Among the approached urban households, 5.7 percent became victims. The average amount of economic losses for approached urban households is 1,345 yuan ($192), and 23,961 yuan ($3,423) for victimized urban households. For victimized urban households, the 25th, 50th and 75th percentiles of economic losses are 300 yuan ($42.3), 1,000 yuan ($141), and 6,000 yuan ($846.2), respectively. Among the approached urban households, 15.4 percent face credit constraint, the average years of schooling is 10.9 years, 38 percent have at least one member with chronic illness, nearly 5 percent are living alone, and 69 percent of urban household heads are male.

5. Empirical Results

5.1 Baseline results

Table 4 presents the baseline OLS results based on equation (1). The dependent variable for columns (1) to (4) is being a fraud victim; the dependent variable for columns (5) to (8) is the logarithm of the total amount of economic losses subject to fraud schemes. Full sample containing all urban households is used in columns (1), (2), (5) and (6). As households are approached by fraudsters before victimization and approached households may have distinct characteristics, we further restrict our sample to approached urban households in columns (3), (4), (7), and (8). Columns (1), (3), (5) and (7) report the results

[14] Netherlands Consumer Authority, "Unfair Commercial Practices (UCPs) in the Netherlands: Survey Report," Prepared by Intomart Gfk, November 2008. See also https://www.ic.gc.ca/eic/site/112.nsf/eng/01513.html.

without any additional control variables, while columns (2), (4), (6) and (8) control for household characteristics. County fixed effects are controlled for in all specifications.

Households being credit constrained is positively correlated with fraud victimization in all specifications. Among the approached households, being credit constrained is significantly associated with 2.3 percentage points increase in the probability of fraud victimization and 20.4 percent (i.e., $e^{0.186}$-1) increase in total amount of economic losses subject to fraud schemes.

Moreover, fraud victimization also correlates with household characteristics. First, household income is negatively associated with fraud victimization. Every 1 percent increase in income is associated with a 0.4 percent decrease in the probability of fraud victimization. Second, we find a *U*-shaped relationship between fraud victimization and household head's age. The probability of fraud victimization reaches its lowest level at household head's age of 43, while younger and older people are more likely to become fraud victims after being approached.[15] Third, respondents suffering from chronic diseases incur larger economic losses subject to fraud schemes. Their desire for better health might make them more vulnerable to expensive health-related fraud schemes.

5.2 IV results

Table 5 presents the 2SLS results. The first and the second stage estimation results are in panels B and A, respectively. The dependent variable is a dummy variable indicating whether the household is a fraud victim in columns (1) to (4), and the logarithm of the total amount of economic losses subject to fraud schemes in columns (5) to (8). Full sample including all urban households is used in columns (1), (2), (5), and (6); restricted sample consisting of the approached urban households is used in columns (3), (4), (7), and (8).

According to the estimation results in panel B, being exposed to the property privatization reform and having a higher local bank density significantly lower the probability of credit constraints. Exposure to the property privatization reform is associated with 3.4 percentage points decrease in the probability of credit constraints. Increasing the number of bank branches within 5km by 100 is associated with about 0.02 percentage points decrease in the likelihood of credit constraints. The F-test statistic for the weak

[15] The older population is more vulnerable because of decreased cognitive function and more free time to participate in social activities that expose them to fraud schemes. The younger population is also more likely to become fraud victims, because they might have less social experience and skills to recognize fraud schemes.

identification test is well above 10, indicating that the instruments are strong (Staiger and Stock, 1997). The Hansen's J statistic and its P-value suggest that we cannot reject the over-identifying restrictions. Estimates from panel A suggest a significant causal impact of credit constraints on fraud victimization. Credit constraints lead to both higher probability of being fraud victims and higher subsequent economic losses.

The estimated effects of credit constraints on fraud victimization are larger for the IV specification than for the OLS specification for plausible reasons. First, the OLS estimates might be biased due to endogeneity. Credit constraints are empirically shown to be positively related to risk aversion. Guiso et al. (1996), for instance, have documented that households with background risk (such as uninsured income risk) may suppress their willingness to bear other avoidable risks. Those households may reduce exposure to risks by reducing investment in risky assets and engagement in risky activities (Cardak and Wilkins, 2009). As risk aversion is associated with lower probability of fraud victimization, the OLS baseline results likely under-estimate the true effects. Second, the IV specification identifies the local average treatment effect (Angrsit and Pischke, 2009). The sample whose credit constraints status is affected by the housing privatization reform and local bank density are those for whom the marginal effects of credit constraints are likely to be greater than those not affected by the reform and the local bank density.

6. Are households randomly approached?

Are households randomly approached by fraudsters? Are being approached by fraudsters and becoming fraud victims jointly determined by common factors? When the household characteristics do not systematically differ between approached and unapproached households, selection bias is not a concern. This might be the case at earlier times when fraudsters chose targets randomly based on telephone numbers or addresses. However, with the development of internet and big data technology, individual information is easily leaked (such as by telecom operators and online shopping websites), and fraudsters could approach households strategically to increase the success ratio.

To explore the differences between the approached and the unapproached households, we first examine the determinants of being approached by fraudsters (approach propensity). Since the recent criminology literature suggests that individuals with certain characteristics are more easily exposed to street crimes and more likely to be attacked by criminals (Langenderfer and Shimp, 2001; Holtfreter et al., 2008; Pratt et al., 2010), we use the following model to examine the determinants of approach propensity.

$$Approach_i = \delta_0 + \delta Credit\_cons_i + \phi X_i + \theta_c + \eta_i \tag{3}$$

Here $approach_i$ is a dummy variable indicating whether the household i was approached by fraudsters last year. X_i refers to the same set of control variables as defined in equation (1). County fixed effects (θ_c) are included. The OLS estimation results using the urban sample are reported in Table 6.

Households are clearly not randomly approached by fraudsters. Households with higher income, worse health conditions, and better education are more likely to be approached by fraudsters. Compared to household heads that are younger and older, those with middle-aged household heads are more likely to be approached. This is perhaps because middle-aged-headed households have a higher level of income, which makes them "better" targets. And middle-aged household heads have more family responsibilities, and thus may engage more in social interactions with potential leaking of private information (i.e., adding strangers as WeChat contacts or follow WeChat public accounts for children's extra-curriculum activities or elder parents' old-age support).

To address the potential selection bias in household approaching, and the possibility that common factors determining both household approaching and fraud victimization, we employ the Heckman selection model (Heckman, 1979). This model first employs the probit model to predict the participation odds, and then introduces an adjustment term to the outcome model to eliminate potential omitted variable bias. To properly implement the Heckman model, the selection model should exploit exogenous variations that influence the participation decision (i.e., being approached) but that are independent of the outcome (i.e., fraud victimization).

We employ the E-commerce coverage at the community level as the exogenous variation that determines the probability of being approached by fraudsters. As mentioned previously, via internet and big data technology, fraudsters now can target individuals more precisely based on leaked private information from telecom operators or online shopping websites. Thus, individuals with frequent online shopping behavior would face a higher vulnerability to fraud schemes (Holtfreter et al., 2008; Reisig and Holtfreter, 2013). In addition, as shown in Table 1, the majority of the fraud schemes are carried out over telephone, indicating that an individual's private information (such as his telephone number or address) is accessible to fraudsters. Online shopping websites may be one of the key channels via which private information gets leaked. It is therefore plausible that living in a community with a higher coverage of E-commerce is associated with a higher probability of private information leakage and being approached by fraudsters. In practice, we employ the average amount of online shopping expenditure at the community level to proxy for E-commerce coverage.

The selection model is as follows:

$$Approach\ propensity_i = \alpha_1 + \kappa E\_commerce_i + \xi X_i + \theta_c + e_i \tag{4}$$

where: $Approach_i = \begin{cases} 1, & if\ Approach\ propensity \geq 0 \\ 0, & if\ Approach\ propensity < 0 \end{cases}$.

The outcome model is:

$$Fraud\ victim_i = \begin{cases} \alpha_2 + \rho Credit\_cons_i + \omega X_i + \theta_c + \mu_i, & if\ Approach_i = 1 \\ 0, & if\ Approach_i = 0 \end{cases} \tag{5}$$

Here $Fraud\ victim_i$ indicates the fraud victimization status of household *i*. The two outcome variables, $Victim_i$ and $lnVictim\_loss_i$, and the key explanatory variable $Credit\_cons_i$ are the same as in equation (1).

In columns (1) to (4) in Table 7, we present the Heckman two-step estimation results. The results of the outcome (fraud victimization) model are shown in panel A. In columns (1) and (2), the dependent variable is a dummy variable indicating fraud victimization. In columns (3) and (4), the dependent variable is the total amount of economic losses subject to fraud schemes. The list of explanatory variables is the same as in the baseline model, except that the inverse mills ratio is added. In panel B, we present the selection model results where *E-commerce coverage* at the community level is treated as the exogenous variation of changes in the probability of being approached by fraudsters. Full sample containing all urban households is used.

Furthermore, we jointly consider the issues of selection bias and the endogeneity of credit constraints indicator by employing the 2SLS strategy. We calculate the inverse mills ratio based on approach propensity, and include this ratio in the regression model where we employ PPR and bank branch as the instrument variables. In this way, we address the issues of selection bias and endogeneity of credit constraints indicator at the same time

(Wooldridge, 2010). The results are in columns (5) to (8) in Table 7. The first and the second stage results of 2SLS are presented in panels B and A, respectively. In columns (5) and (6), the dependent variable is a dummy variable indicating fraud victimization. In columns (7) and (8), the dependent variable is the total amount of economic losses subject to fraud schemes. The full sample containing all urban households is used in columns (5) and (7), while the restricted sample consisting of approached urban households is used in columns (6) and (8). In all specifications in Table 7, county fixed effects are included and standard errors are clustered at the city level.

Based on the selection model (columns (1) to (4) of panel B in Table 7), the *E-commerce coverage* at the community level is a good predictor of fraud approaching. The coverage of community *E-commerce* is significantly and positively associated with the probability of being approached by fraudsters. More importantly, after considering the potential selection bias, the relationship between credit constraints and fraud victimization still holds. The probability of becoming fraud victims and the total amount of economic losses are both significantly higher for households with credit constraints, and the coefficients are similar to the baseline regression results in Table 5.

When dealing with the endogeneity of credit constraints indicator and sample selection bias jointly (columns (5) to (8) in Table 7), our baseline regression results remain robust. In comparison with Table 5, the coefficients of credit constraints and other explanatory variables are largely the same. Credit-constrained households are more likely to become fraud victims with a larger amount of subsequent economic losses. In all specifications, the F-test statistic for the weak identification test is well above 10, and the Hansen's J statistic and its P-value suggest that we cannot reject the over-identifying restrictions.

7. Alternative Interpretation: Information Acquisition and Financial Literacy

A concern about our previous findings is that fraud victimization is not affected by credit constraints but by anti-fraud information acquisition, which is correlated with credit constraints. With widespread fraud schemes in China, many local governments and law enforcement institutions have initiated anti-fraud campaigns. Since victims often transfer money to fraudsters via banks, many banks take the responsibility of anti-fraud education. Indeed, smart-phone users often receive reminders from their bank branches on the need to be mindful of fraud schemes. Households with limited access to formal credits may thus miss the chance of acquiring anti-fraud information, and are unable to recognize the fraud schemes when facing fraudsters.

To address this concern, we add in the model two measures on household information acquisition. The first measure captures the intensity of information acquisition based on CHFS's question about the intensity with which the respondent follows economic/financial news from the media. Five options are provided: from 'extremely intensive' to 'never paying attention' (corresponding value from 1 to 5). Households that intensively follow economic/financial news would obtain greater amount of anti-fraud information. The second measure is total household expenditure on internet, magazine, newspaper and other information sources. Households with a higher amount of such expenditure are more likely to acquire anti-fraud information.

Another concern is that the relationship between credit constraints and fraud victimization may be driven by the omission of financial literacy. On the one hand, a higher level of financial literacy is associated with a higher likelihood of obtaining bank loans (Lyons et al., 2019; Xu et al., 2019) and a lower likelihood of engaging in high-cost borrowing and using informal financial services (Disney and Gathergood, 2013; Lusardi and Scheresberg, 2013). A higher level of financial literacy also helps people better understand financial products and make better financial decisions about taking advantage of formal financial services. Financial literacy thus should relieve credit constraints. On the other hand, financial literacy should help households distinguish between fraud schemes and high returns from legitimate investment projects, and thus lower the chance of fraud victimization.

To address this concern of omitted variable bias, following the previous literature (Van Rooij, 2011; Lusardi and Mitchell, 2008), we add two measures for financial literacy in the model. CHFS has a series of questions designed to measure respondents' financial literacy.[16] The first measure is a dummy variable that equals to 1 if the respondent

[16] The first question regarding financial literacy is: assume the annual interest rate of the bank is 4 percent, if you deposit 100 yuan in the bank for one year, how much do you have one year later? The second question is: suppose the annual interest rate of the bank is 5 percent, and the inflation rate is 3 percent, after saving 100 yuan in your bank account for one year, can you buy more or less than last year?

correctly answers all questions related to financial literacy. The second measure is the total number of correct answers.

The OLS and the 2SLS results are presented in panels A and B in Table 8, respectively. In columns (1) to (4), the dependent variable is a dummy variable indicating fraud victimization. In columns (5) to (8), the dependent variable is the total amount of economic losses subject to fraud schemes. In columns (1), (2), (5) and (6), we address the effect of information acquisition, alternatively including the categorical variable (*Inf. Acq*) to indicate economic/financial news acquirement intensity or households' information acquisition-related expenditure (*Internet exp*, in logarithm). In columns (3), (4), (7) and (8), we address the effect of financial literacy by alternatively including the two proxies of financial literacy.

The results suggest that neither information nor financial literacy is the driving force of fraud victimization. The effect of credit constraints on fraud victimization is robust to various specifications. Similar to our main results, the probability of becoming fraud victims is 2.3 percentage points higher and the total amount of economic losses is 20.3 percent higher for households with credit constraints.

8. Potential Mechanisms

As discussed in our conceptual framework, a potential channel for credit constraints to affect fraud victimization is personal discount rate (impatience). Testing whether being credit constrained is associated with higher discount rates requires a proper proxy. Previous studies have designed several methods to measure the discount rate. The simplest one is the Money Earlier or Later (MEL) choice, where respondents need to choose between smaller, immediate payments and larger, later payments (Pender, 1996; Harrison et al., 2002; Tanaka et al., 2010; Courtemanche et al., 2015).[17] Another strand of literature conducts field studies to infer the discount rate from the real world that involves personal intertemporal trade-offs (Viscusi and Moore, 1989; DellaVigna and Paserman, 2005; Busse et al., 2013; Bisin and Hyndman, 2020; Schilbach, 2019).[18] Ashraf et al. (2006) point out

[17] Other experimental methods similar to MEL include the matching tasks, pricing tasks and rating tasks. (see Frederick et al. (2002) for more details).

[18] By observing workers' choice on whether accepting a risker job with higher salary, Viscusi and Moore (1989) study the trade-off between the quality and expected length of life to elicit the discount rate.

that a household saving account (especially time deposit account) requires an intertemporal trade-off between current and later rewards/consumption. Similarly, we can infer the discount rate by examining illiquid accounts of households. Illiquid accounts usually have higher returns but require delayed gratification/consumption. Therefore, having illiquid accounts implies a higher level of patience. Since having illiquid accounts (usually with higher returns) by itself could just reflect a household's higher income level and human capital, it is essential to control for income and human capital when using having illiquid accounts to proxy patience. In practice, we use three measures for the discount rate, including an indicator for having an illiquid account, the amount of illiquid assets, and the ratio of illiquid assets over total assets.

The OLS and 2SLS estimation results are shown in columns (1) to (3) in Table 9. In all specifications, our controls include the level of household income and of human capital. Credit constraints are found to robustly lead to a lower probability of having an illiquid account, a lower value of illiquid asset, and a lower ratio of illiquid asset in total asset. Households with credit constraints thus have significantly higher discount rates than households without credit constraints. The finding is consistent with the notion that credit-constrained households are more likely to fall for fraud schemes that promise high current returns partly because of their high discount rates.

Another possible channel is the need for social network expansion. To obtain sufficient credit, households with limited access to formal credit would engage in activities to expand their social networks to possess social collateral, which might in turn encourage people to behave more cooperatively. Therefore, when encountering disguised fraud schemes, they are more likely to become victims.

We first test whether households with limited access to formal credit are more likely to use informal credit to satisfy credit needs. We construct an indicator for using informal credit (*Informal dummy*). As social network expansion normally involves frequent transportation and communication, we then use the ratio of household expenditure in

DellaVigna and Paserman (2005) find that impatient workers have shown different levels of effort in job search than patient workers. Other studies on intertemporal choices address behaviors such as willingness to pay for more fuel efficient cars (Busse et al., 2013), commitments to work deadlines (Bisin and Hyndman, 2014), demand for commitment to sobriety (Schilbach, 2019), and allocation to liquid and illiquid accounts (Ashraf et al., 2006; Beshears et al., 2015).

commuting and telephone services over total household expenditure (*Social_exp*) to measure the efforts for social network expansion. Although the data on cooperation level when facing fraud schemes is not available, we use the survey interviewer's assessment about households' compliance to proxy the general cooperation level (*Cooperation*), which is a dummy variable that equals to 1 if the household respondent was assessed as very compliant during the interview.

Both the OLS and the 2SLS estimation results are reported in columns (4) to (6) in Table 9. The results are consistent with our conjecture. Credit-constrained households are more likely to use informal credit. Perhaps to facilitate the necessary social connections needed in informal borrowing, credit constrained households spend more on commuting and telephone services, and are more likely to behave cooperatively. The finding here that credit-constrained households tend to behave more cooperatively is consistent with a calculation that we made that a significant proportion (70%) of fraud victims attribute their victimization to trust and compliance.[19]

9. Conclusion

Using a novel and comprehensive data set on fraud victimization from CHFS, we investigate the extent to which urban households' financial conditions affect fraud victimization, and then explore potential mechanisms. The baseline regression results indicate that household credit constraints are associated with 2.3 percentage points higher probability of becoming a fraud victim and 20.4 percent higher economic losses among those being approached. To deal with endogeneity issues, we employ the IV approach, and use as instrumental variables the exposure to an unexpected nation-wide private property reform and the local bank density. To address potential sample selection bias, we further use the Heckman selection model where e-commerce coverage at the community level is used as the source of exogenous variations. The findings suggest that household credit constraints lead to both a higher probability of fraud victimization and higher subsequent economic losses upon being approached. Further analyses on potential mechanisms show that the personal discount rate (impatience) and the need for social network expansion are likely pathways via which credit constraints affect fraud victimization. Our paper thus

[19] Authors' calculation based on CHFS data.

points to a key disadvantage in relying on informal credit networks: the risk of being vulnerable to fraud and the consequent losses.

The current study has implications for anti-fraud policy. Current policies on combating fraud victimization emphasize anti-fraud campaigns and increasing financial literacy, or more generally in the case of containing crimes, strengthening law enforcement and improving the legal environment were thought to be effective to defeat crimes (Ehrlich, 1996; Levitt, 1997; Di Tella and Schargrodsky, 2004). We provide complementary perspective and evidence that policies focusing on the provision of financial services and credit to households may be as important. When encountering credit-related fraud schemes, sufficient access to credit provided to households would greatly reduce the risk of exposure to fraud schemes and allow these households to exhibit more patience—or be less subject to the temptation of quick payoffs.

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Table 1: Summary Statistics of Fraud Approaching

=1 if fraud-approached households (HHs)	Obs.	Mean	Std.Dev	Min	Max
Approached urban HHs	25,635	0.674	0.469	0	1
- Over Phone	25,635	0.651	0.477	0	1
- Through text	25,635	0.141	0.348	0	1
- Face-to-face	25,635	0.080	0.272	0	1

Note: This table describes the probability of urban households being approached by fraudsters. We classify the intermedium through which urban households were approached into telephone, texting (i.e., SMS, mail, and e-mail), and face-to-face contacts.

Table 2: Fraud Victimization Differences

	(1)	(2)	(3)	(4)	(5)
	Difference between credit constrained and un-constrained urban HHs				
=1 if Fraud victim dummy	All urban HHs	Urban constrained	Urban un-constrained	Diff.	t-stat.
Approached urban HHs	0.057	0.079	0.053	0.026	5.240***

Note: This table describes differences in the probability of fraud victimization after being approached by fraudsters. We focus on urban households with and without credit constraints. We report the probability of being a fraud victim after being approached by fraudsters for all urban households, urban households with credit constraints, urban households without credit constraints and the difference in columns (1) to (4). The last column reports the t statistics for t-test. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Definitions and Summary Statistics of Key Variables

Variables	Definitions	Obs	Mean	Std.Dev	Min	Max
Panel A: all urban HHs						
Victim	=1 if fraud victim	25,635	0.038	0.191	0	1
Victim_loss	Economic loss subject to fraud (1,000 RMB Yuan)	25,630	0.897	29.886	0	3000
Credit_cons	=1 if credit constraint	25,635	0.159	0.366	0	1
Panel B: approached urban HHs						
Victim	=1 if fraud victim	17,087	0.057	0.231	0	1
Victim_loss	Economic loss subject to fraud (1,000 RMB Yuan)	17,082	1.345	36.600	0	3000
Victim_loss (>0)	Economic loss subject to fraud (1,000 RMB Yuan)	959	23.961	152.779	0.004	3000
lnVictim_loss	Economic loss S.t. fraud(in log)	17,087	0.412	1.771	0	14.914
Credit_cons	=1 if credit constraint	17,087	0.154	0.360	0	1
Lincome	Household total income (RMB Yuan, in log)	16,433	10.891	1.279	0	18.421
Head age	House head age	17,087	51.454	14.943	16	90
Schooling	Head years of schooling	17,087	10.769	3.942	0	22
Illness	=1 if head is ill	17,087	0.380	0.485	0	1
Alone	=1 if head is living alone	17,087	0.046	0.209	0	1
Male	=1 if head is male	17,087	0.687	0.464	0	1
Branch	total # of bank institutions within 5 kilometers (in 1,000)	16,439	0.103	0.096	0	0.444
PPR	=1 if experienced Property Privatization Reform	17,087	0.186	0.389	0	1
log(Internet exp.)	expenditure in internet (in log)	16,377	3.891	1.820	0	11.002
Finan. Literacy						
- correct D	=1 if correctly answers all questions	17,087	0.116	0.320	0	1
- correct #	total number of correct answers	17,087	0.489	0.694	0	2
Illiquid dummy	=1 if having an illiquid account	17,087	0.257	0.437	0	1
log(Illiquid asset)	the amount of illiquid asset (in log)	16,978	2.781	4.820	0	16.811
Illiquid/total asset	the ratio of illiquid asset over total asset	16,507	0.182	0.334	0	1
Social_exp	expenditure in commuting +telephone services / total expenditure	16,206	0.008	0.008	0	0.050
Informal dummy	=1 if using informal credit	17,087	0.208	0.406	0	1
Cooperation	=1 if compliant during the interview	17,087	0.576	0.494	0	1

Note: This table describes the summary statistics for key variables. All urban households are included in panel A. Approached urban households are included in panel B. *Victim* is a dummy variable that equals to 1 if a household has been a victim of fraud, *Victim_loss* measures the total economic loss subject to fraud scheme, *Credit_cons* is a dummy variable indicating whether household is credit constrained. Being credit constrained is defined as unable to borrow money for any of the following reasons: (a) need loan, but rejected by bank or other credit institutions; (b) unable to obtain sufficient loan from bank or other credit institutions; (c) didn't apply for loan because no collateral/complex paperwork/outstanding loan/maybe rejected. *Lincome* is the logarithm of the total sum of household income, which consists of labor income, business income, agriculture income, investment income, transfer income and other income. *Schooling* is the years of schooling for the household head. *Illness* is a dummy variable to indicate if the household head suffers from at least one chronic disease, such as hypertension, hyperlipidemia, diabetes, stroke, heart disease, mental issue, Alzheimer's disease, and Parkinson. *Alone* is a dummy variable to indicate whether the household head lives alone. And *Male* equals to 1 if respondent is male. *PPR* is the property privatization reform experience dummy which equals to 1 if household members working in various level of state owned enterprises or the government in 1994. *Branch* is the local bank density, which is measured by the total number of bank institutions (in 1,000) within 5 kilometers of the households' current residence. Internet exp. is measured by total household expenditure on internet, magazine, newspaper and other information sources. Financial literacy (correct D) equals to 1 if the respondent correctly answers all questions related to financial literacy, financial literacy (correct #) is the total number of correct answers. Illiquid dummy equals to 1 if households possess illiquid account, illiquid asset is the amount of illiquid asset, and illiquid asset/total asset is the ratio of illiquid asset over total asset. Social_exp. is the ratio of household expenditure in commuting and telephone services over total household expenditure. Informal dummy is an indicator for using informal credit. Cooperation is a dummy variable and equals to 1 if households were very compliant during the interview.

Table 4: Credit Constraint and Fraud Victimization: OLS results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All HHs		Approached HHs		All HHs		Approached HHs	
	dummy of being fraud victim				lnVictim_loss			
Credit_cons	0.017^{***}	0.017^{***}	0.024^{***}	0.023^{***}	0.137^{***}	0.136^{***}	0.191^{***}	0.186^{***}
	(0.004)	(0.004)	(0.006)	(0.006)	(0.030)	(0.030)	(0.046)	(0.045)
Lincome		-0.001		-0.004^{*}		0.003		-0.013
		(0.001)		(0.002)		(0.009)		(0.015)
Head age		-0.002^{***}		-0.003^{***}		-0.013^{**}		-0.024^{***}
		(0.001)		(0.001)		(0.005)		(0.008)
Head age sq.		$1.9*10^{-5**}$		$3.5*10^{-5***}$		$1.4*10^{-4\,**}$		$2.5*10^{-4\,***}$
		$(6*10^{-6})$		$(1*10^{-5})$		$(4.9*10^{-5})$		$(7.4*10^{-5})$
Illness		0.006^{**}		0.006		0.056^{**}		0.060^{*}
		(0.003)		(0.005)		(0.022)		(0.033)
Alone		0.006		0.014		0.040		0.091
		(0.007)		(0.011)		(0.056)		(0.085)
Male		-0.003		-0.004		-0.027		-0.037
		(0.003)		(0.004)		(0.023)		(0.033)
Schooling		0.000		-0.001		0.002		-0.006
		(0.000)		(0.001)		(0.003)		(0.005)
Constant	0.035^{***}	0.081^{***}	0.053^{***}	0.174^{***}	0.253^{***}	0.483^{***}	0.383^{***}	1.090^{***}
	(0.001)	(0.021)	(0.001)	(0.033)	(0.005)	(0.164)	(0.007)	(0.252)
County D.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	25635	24472	17087	16433	25635	24472	17087	16433
R2	0.0188	0.0206	0.0333	0.0378	0.0189	0.0208	0.0319	0.0357

Note: This table presents the baseline relationship of credit constraints and fraud victimization using OLS, and the sample of all urban households is used. The dependent variable for columns (1) to (4) is being a fraud victim; the dependent variable for columns (5) to (8) is the total amount of economic loss subject to fraud scheme. Full sample containing all households is used in columns (1), (2), (5) and (6). As households are approached by fraudsters before victimization and approached households may have distinct characteristics, we further restrict our sample to approached households in columns (3), (4), (7), and (8). County fixed effects are controlled for in all specifications. *Credit_cons* is a dummy variable indicating whether household is credit constrained. Being credit constrained is defined as unable to borrow money for any of the following reasons: (a) need loan, but rejected by bank or other credit institutions; (b) unable to obtain sufficient loan from bank or other credit institutions; (c) didn't apply for loan because no collateral/complex paperwork/outstanding loan/maybe rejected. *Lincome* is the logarithm of the total sum of household income, which consists of labor income, business income, agriculture income, investment income, transfer income and other income. *Schooling* is the years of schooling for the household head. *Illness* is a dummy variable to indicate if the household head suffers from at least one chronic disease, such as hypertension, hyperlipidemia, diabetes, stroke, heart disease, mental issue, Alzheimer's disease, and Parkinson. *Alone* is a dummy variable to indicate whether the household head lives alone. And *Male* equals to 1 if respondent is male. Robust standard errors are in parenthesis, and are clustered at city level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 Credit Constraint and Fraud Victimization: 2SLS estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 2nd stage	dummy of being a fraud victim				lnVictim_loss			
	All HHs		Approached HHs		All HHs		Approached HHs	
Credit_cons	0.099*	0.191**	0.225***	0.363**	0.479	1.177*	1.277**	2.299**
	(0.057)	(0.090)	(0.077)	(0.142)	(0.464)	(0.713)	(0.627)	(1.101)
Lincome		-0.000		-0.003		0.005		-0.006
		(0.001)		(0.002)		(0.009)		(0.016)
Head age		-0.002***		-0.004***		-0.015**		-0.029***
		(0.001)		(0.001)		(0.006)		(0.009)
Head age sq		$2.7*10^{-5***}$		$5.1*10^{-5***}$		$1.8*10^{-4**}$		$3.5*10^{-4***}$
		$(8*10^{-6})$		$(1.3*10^{-5})$		$(6.5*10^{-5})$		$(1*10^{-4})$
Illness		0.000		-0.005		0.022		-0.004
		(0.004)		(0.006)		(0.030)		(0.043)
Alone		0.003		0.008		0.022		0.058
		(0.008)		(0.013)		(0.059)		(0.095)
Male		-0.009*		-0.013**		-0.062*		-0.094**
		(0.004)		(0.006)		(0.033)		(0.048)
Schooling		0.001*		0.001		0.010		0.009
		(0.001)		(0.001)		(0.006)		(0.011)
Panel B: 1st stage	Endogenous variable: credit constraint							
Branch	-0.298***	-0.199***	-0.274***	-0.154**	-0.298***	-0.199***	-0.274***	-0.154**
(within 5km)	(0.082)	(0.073)	(0.083)	(0.076)	(0.082)	(0.073)	(0.083)	(0.076)
PPR	-0.056***	-0.036***	-0.052***	-0.034***	-0.056***	-0.036***	-0.052***	-0.034***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
County dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24701	23587	16439	15818	24701	23587	16439	15818
Weak IV (F Stat.)	70.37	26.55	46.33	15.24	70.37	26.55	46.33	15.24
Over Ident. (Hansen J)	0.166	0.00001	0.061	0.043	0.076	0.023	0.006	0.177
Over Ident. (P-Value)	0.684	0.997	0.805	0.835	0.783	0.880	0.939	0.674

Note: This table reports the 2SLS estimates of the effect of credit constraints on fraud victimization, and the sample of urban households is used. The first instrumental variable is property privatization reform experience dummy (PPR) which equals to 1 if household members working in various level of state owned enterprises or government before the reform, the second instrument variable is bank density, which is measured by the total number of bank institutions (in 1,000) within 5 kilometers of households' current residence (Branch). Panel A shows the 2nd stage while Panel B presents the 1st stage results. The dependent variable is a dummy variable indicating whether the household is a fraud victim in columns (1) – (4), while for columns (5) – (8), it is the total amount of economic losses subject to fraud scheme. Full sample including all households is used in columns (1), (2), (5), and (6), and restricted sample compromised of approached households is used in columns (3), (4), (7), and (8). We also report weak IV test statistics (F statistics) and over identification test statistics (Hansen J statistics and corresponding P-value). *Credit_cons* is a dummy variable indicating whether household is credit constrained. Being credit constrained is defined as unable to borrow money for any of the following reasons: (a) need loan, but rejected by bank or other credit institutions; (b) unable to obtain sufficient loan from bank or other credit institutions; (c) didn't apply for loan because no collateral/complex paperwork/outstanding loan/maybe rejected. *Lincome* is the logarithm of the total sum of household income, which consists of labor income, business income, agriculture income, investment income, transfer income and other income. *Schooling* is the years of schooling for the household head. *Illness* is a dummy variable to indicate if the household head suffers from at least one chronic disease, such as hypertension, hyperlipidemia, diabetes, stroke, heart disease, mental issue, Alzheimer's disease, and Parkinson. *Alone* is a dummy variable to indicate whether the household head lives alone. And *Male* equals to 1 if respondent is male. County fixed effects are controlled for in all specifications. Robust standard errors are clustered at city level and reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Determinants of being approached by fraudsters: OLS

	(1)
Y=1 if approached by fraudsters	Urban HHs
Credit_cons	0.028***
	(0.008)
Lincome	0.023***
	(0.003)
Head age	0.004***
	(0.001)
Head age sq	$-4.4*10^{-5}$ ***
	$(1.1*10^{-5})$
Illness	0.038***
	(0.007)
Alone	-0.037***
	(0.011)
Male	-0.014**
	(0.007)
Schooling	0.012***
	(0.001)
Constant	0.226***
	(0.041)
County Dummy	Yes
Observations	24472
R-squared	0.161

Note: This table shows the determinants of being approached by fraudsters. The explained variable is a dummy variable indicating weather a household has been approached by fraudster. The full urban sample containing all households is used. *Lincome* is the logarithm of the total sum of household income, which consists of labor income, business income, agriculture income, investment income, transfer income and other income. *Schooling* is the years of schooling for the household head. *Illness* is a dummy variable to indicate if the household head suffers from at least one chronic disease, such as hypertension, hyperlipidemia, diabetes, stroke, heart disease, mental issue, Alzheimer's disease, and Parkinson. *Alone* is a dummy variable to indicate whether the household head lives alone. And *Male* equals to 1 if respondent is male. County fixed effects are controlled for in all specifications. Robust standard errors are clustered at city level and reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7 Credit Constraint and Fraud Victimization: Check on Selection Bias

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A:	Heckman (twostep): outcome model				2SLS: 2nd stage			
	Dummy of being fraud Victim		lnVictim_loss		Dummy of being fraud Victim		lnVictim_loss	
	All HHS				All HHs	Approached HHs	All HHs	Approached HHs
Credit_cons	0.021^{***}	0.023^{***}	0.168^{***}	0.181^{***}	0.191^{**}	0.323^{**}	1.179^{*}	2.050^{*}
	(0.005)	(0.005)	(0.041)	(0.040)	(0.090)	(0.140)	(0.711)	(1.086)
Lincome		0.006^{**}		0.040^{**}	0.001	0.006^{*}	0.013	0.044^{*}
		(0.003)		(0.019)	(0.002)	(0.003)	(0.015)	(0.025)
Head age		-0.002^{*}		-0.014^{**}	-0.002^{**}	-0.003^{**}	-0.014^{**}	-0.019^{**}
		(0.001)		(0.007)	(0.001)	(0.001)	(0.007)	(0.009)
Head age sq		$1.7*10^{-5***}$		$1.4*10^{-4\,***}$	$2.4*10^{-5***}$	$3.2*10^{-5***}$	$1.7*10^{-4\,**}$	$2.4*10^{-4\,***}$
		$(9.3*10^{-6})$		$(6.7*10^{-5})$	$(1*10^{-5})$	$(1.4*10^{-5})$	$(7.2*10^{-5})$	$(1 *10^{-4})$
Illness		0.021^{***}		0.147^{***}	0.002	0.010	0.029	0.078
		(0.006)		(0.043)	(0.005)	(0.007)	(0.035)	(0.050)
Alone		0.000		0.010	0.001	-0.003	0.013	-0.004
		(0.011)		(0.078)	(0.008)	(0.013)	(0.063)	(0.100)
Male		-0.007		-0.055	-0.008^{*}	-0.015^{**}	-0.059^{*}	-0.104^{**}
		(0.005)		(0.035)	(0.004)	(0.006)	(0.033)	(0.047)
Schooling		0.004^{***}		0.022^{**}	0.002^{**}	0.005^{***}	0.014^{*}	0.033^{**}
		(0.001)		(0.008)	(0.001)	(0.002)	(0.008)	(0.013)
Inverse Mills	0.125^{***}	0.266^{***}	0.707^{***}	1.546^{***}	0.041	0.246^{***}	0.176	1.400^{***}
	(0.019)	(0.055)	(0.146)	(0.413)	(0.036)	(0.071)	(0.265)	(0.493)
Panel B	Heckman (twostep): selection model				2SLS: 1st stage			
	Dummy of Being approached				Endogenous variable: credit constraint dummy			
E-Commerce Coverage	0.050^{***}	0.050^{***}	0.050^{***}	0.050^{***}				
	(0.010)	(0.010)	(0.010)	(0.010)				
Branch (within 5km)					-0.178^{**}	-0.140^{*}	-0.178^{**}	-0.140^{*}
					(0.072)	(0.077)	(0.072)	(0.077)
PPR					-0.035^{***}	-0.033^{***}	-0.035^{***}	-0.033^{***}
					(0.006)	(0.007)	(0.006)	(0.007)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23737	23737	23737	23737	22877	15298	22877	15298
Weak IV (F Stat.)					24.31	14.13	24.31	14.13
Hansen J					0.005	0.002	0.019	0.059
-P-value					0.945	0.964	0.891	0.808

Note: This table report the result of selection bias correction for our benchmark results, all urban residents are in the sample. We employ Heckman selection strategy to deal with selection bias issue, in column (1) – (4), we reports the results of Heckman selection model, panel A lists the results of outcome model, in panel B, the selection model is presented, the explained variable for column (1) and (2) is fraud victimization dummy, which equals to 1 if household have been a victim of fraud, while explained variable for column (3) and (4) is amount of economic loss subject to fraud scheme. In column (5) –(8), we employ 2SLS to consider the endogeneity of credit constraint and sample selection bias jointly, in panel A, we present the 2nd stage results of 2SLS, and reports 1st stage of 2SLS in panel B, the explained variable for column (5) and (6) is fraud victimization dummy, while explained variable for column (7) and (8) is amount of economic loss subject to fraud scheme, in column (5) and (7), all households are used in our analysis, and we restricted our analysis in column (6) and (8) to households that have been approached by fraudsters, we also report weak IV test statistics (F statistics) and over identification test statistics (Hansen J statistics and corresponding P-value). *Credit_cons* is a dummy variable indicating whether household is credit constrained. Being credit constrained is defined as unable to borrow money for any of the following reasons: (a) need loan, but rejected by bank or other credit institutions; (b) unable to obtain sufficient loan from bank or other credit institutions; (c) didn't apply for loan because no collateral/complex paperwork/outstanding loan/maybe rejected. *Lincome* is the logarithm of the total sum of household income, which consists of labor income, business income, agriculture income, investment income, transfer income and other income. *Schooling* is the years of schooling for the household head. *Illness* is a dummy variable to indicate if the household head suffers from at least one chronic disease, such as hypertension, hyperlipidemia, diabetes, stroke, heart disease, mental issue, Alzheimer's disease, and Parkinson. *Alone* is a dummy variable to indicate whether the household head lives alone. And *Male* equals to 1 if respondent is male. E-commerce coverage is our exogenous variation to predict the probability of being approached by fraudsters, it is measured by the average amount of online shopping expenditure last month at community level. County fixed effects are controlled for in all specifications. Robust standard errors are clustered at city level and reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8 credit constraint and fraud victimization: alternative explanations

approached HHs	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: OLS	dummy of being fraud victim				lnVictim_loss			
Credit_cons	0.023***	0.022***	0.023***	0.023***	0.186***	0.182***	0.185***	0.185***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.045)	(0.047)	(0.045)	(0.045)
Inf. Acq=2	-0.005				-0.069			
	(0.012)				(0.091)			
Inf. Acq=3	-0.007				-0.081			
	(0.010)				(0.083)			
Inf. Acq=4	-0.017*				-0.137*			
	(0.010)				(0.077)			
Inf. Acq=5	-0.013				-0.127			
	(0.011)				(0.085)			
Log(internet exp)		-0.000				-0.001		
		(0.001)				(0.010)		
Finan. Literacy			0.014**				0.073	
(correct d)			(0.007)				(0.050)	
Finan. Literacy				0.007**				0.033
(correct #)				(0.003)				(0.023)
county dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: 2SLS (2nd stage)								
Credit_cons	0.318**	0.320**	0.326**	0.327**	2.017*	2.034*	2.064*	2.070*
	(0.137)	(0.137)	(0.139)	(0.139)	(1.063)	(1.049)	(1.079)	(1.082)
Inf. Acq=2	-0.003				-0.064			
	(0.013)				(0.093)			
Inf. Acq=3	0.002				-0.027			
	(0.011)				(0.082)			
Inf. Acq=4	-0.004				-0.058			
	(0.011)				(0.084)			
Inf. Acq=5	-0.002				-0.062			
	(0.012)				(0.093)			
Log(internet exp)		0.000				0.001		
		(0.002)				(0.011)		
Finan. Literacy			0.014*				0.074	
(correct D.)			(0.008)				(0.057)	
Finan. Literacy				0.006				0.025
(correct #)				(0.003)				(0.027)
county dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ivs. Mills	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15288	14744	15298	15298	15288	14744	15298	15298
Weak IV F. stat	14.24	13.91	14.16	14.15	14.24	13.91	14.16	14.15
Over Ident.	0.0002	0.131	$8*10^{-5}$	$2*10^{-4}$	0.090	0.311	0.077	0.072
(Hansen J)								
-p-value	0.990	0.718	0.998	0.997	0.765	0.577	0.781	0.789

Note: This table reports the results of credit constraint and fraud victimization after ruling out alternative explanations, we employ urban households that are approached by fraudsters as our sample, the models are estimated using OLS in Panel A, 2SLS in panel B. The explained variable for the first four columns is fraud victim dummy, while the explained variable for last four columns is economic loss of fraud. *Credit_cons* is a dummy variable indicating whether household is credit constrained. *Lincome* is the logarithm of the total sum of household income. *Schooling* is the years of schooling for the household head. *Illness* is a dummy variable to indicate if the household head suffers from at least one chronic disease. *Alone* is a dummy variable to indicate whether the household head lives alone. And *Male* equals to 1 if respondent is male. In column (1) and (5), we controlled household information acquisition dummy variables to the model, in column (2) and (6), we alternatively uses total amount of (in log) expenditure on internet, magazine, newspapers as proxy for information acquisition. In column (3) and (7), we add financial literacy dummy variable which equals to one if respondent answer questions correctly regarding financial calculation, while in column (4) and (8), we proxy financial literacy by using total number of correct answer. In Panel B, we also included inverse mills ratio in all specifications to rule out potential selection issue, which is discussed in selection bias section, and we also reported weak IV test statistics (F statistics) and over identification test statistics (Hansen J statistics and corresponding P-value). County fixed effects are controlled for in all specifications. Robust standard errors are clustered at city level and reported in parenthesis. * *p < 0.1, ** p < 0.05, *** p < 0.01.*

Table 9 mechanism

Approached HHs	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS	Illiquid dummy	Log (1+ Illiquid asset)	Illiquid asset / total asset	Informal dummy	Social_exp	Cooperation
Credit_cons	-0.053***	-0.602***	-0.038***	0.327***	0.001***	0.052***
	(0.009)	(0.105)	(0.008)	(0.013)	(0.000)	(0.011)
county dummy	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16433	16330	15907	16433	15618	16433
R-sq	0.106	0.114	0.115	0.214	0.103	0.0890
Panel B: 2SLS (2nd stage)						
Credit_cons	-0.685***	-7.755***	-0.588***	1.635***	0.010**	0.808***
	(0.261)	(2.857)	(0.224)	(0.368)	(0.005)	(0.309)
County dummy	Yes	Yes	Yes	Yes	Yes	Yes
Ivs. Mills	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15298	15210	14836	15298	14594	15298
Weak IV F. stat	14.10	13.55	13.57	14.10	13.01	14.10
Over Ident.(Hansen J)	0.888	0.713	1.387	0.169	4.112	0.0180
Hansen J. p-value	0.346	0.398	0.239	0.681	0.0426	0.893

Note: This table discuss the potential mechanism of credit constraint and fraud victimization, we employ urban households that are approached by fraudsters as our sample. Two alternative mechanisms are discussed, personal discount rate and social network expansion. Column (1) – (3) discuss the potential mechanism from the perspective of discount rate, the explained variables are possession of illiquid account dummy, amount of illiquid account and the ratio of illiquid to proxy discount rate, respectively. In column (4), we use a dummy variable (*informal dummy*) to indicate whether households have borrow money from informal source. The explained variable for column (5) is social activity intensity (*Social_exp*), which is defined as the ratio of household expenditure in commute and telephone services over total consumption. In column (6), we use a dummy variable (*Cooperation*) to indicate whether the households behave cooperatively during the interview. We estimate the models using OLS in panel A, while 2SLS in panel B. *Credit_cons* is a dummy variable indicating whether household is credit constrained. *Lincome* is the logarithm of the total sum of household income, which consists of labor income, business income, agriculture income, investment income, transfer income and other income. *Schooling* is the years of schooling for the household head. *Illness* is a dummy variable to indicate if the household head suffers from at least one chronic disease, such as hypertension, hyperlipidemia, diabetes, stroke, heart disease, mental issue, Alzheimer's disease, and Parkinson. *Alone* is a dummy variable to indicate whether the household head lives alone. And *Male* equals to 1 if respondent is male.. In panel B, we additional control inverse mills ratio to rule out potential selection bias issue, we also reported weak IV test statistics (F statistics) and over identification test statistics (Hansen J statistics and corresponding P-value). County fixed effects are controlled for in all specifications. Robust standard errors are clustered at city level and reported in parenthesis * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.