Regional Power: Consumption Responses to Local Dishonest Judgment Debtors

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Abstract

Using transaction-level credit card spending from a leading Chinese commercial bank, we show that consumers reduce their consumption by 10.39% when the number of local dishonest judgment debtors increases by one percentage point. The consumption response is spatially highly concentrated, immediate, and not persistent. Additionally, our findings cannot be explained by changes in personal background risks and macroeconomic status. Rather than a decrease in credit supply, we find that the number of local dishonest judgment debtors triggers an active downward adjustment in consumption through a decrease in credit demand. To address endogeneity concerns, we perform a difference-in-difference analysis.

Keywords: dishonest judgment debtors, consumer spending, credit cards, experiences

JEL Classification: D12, D91, G21, G28

1. Introduction

Consumer choices are influenced by a variety of factors, ranging from personal experiences to broader economic variables, like income shocks (Jappelli and Pistaferri, 2010), housing wealth (Campbell and Cocco, 2007; Di Maggio et al., 2017), monetary policy (Kaplan, Moll, and Violante, 2018), and peer behavior (Agarwal, Qian, and Zou, 2020), etc. Some studies suggest that local experiences, such as variations in house prices and employment rates, significantly impact individual consumption expectations and behaviors (Kuchler and Zafar, 2019). Empirical evidence also suggests that social influence information, especially from local sources such as neighbors' accidental lottery wins or personal bankruptcy experiences (Agarwal et al., 2020; 2021), has a more pronounced impact on individuals' consumption decisions than information derived from distant sources. This paper aims to explore a crucial yet understudied piece of evidence in this area that shows how consumption is influenced by regional factors, such as the number of dishonest judgment debtors in a consumer's local environment and provides insight into consumer decision-making dynamics in diverse geographical contexts.

In this paper, we investigate how a change in the number of dishonest judgment debtors in a consumer's local environment affects consumption behavior in the short term[2]. In October 2013, the Supreme People's Court began publishing a list of dishonest judgment debtors, which refers to individuals who, despite the capacity to do so, fail to fulfill court orders and their legal obligations. Additionally, courts at all levels are authorized to publish the list of dishonest judgment debtors through newspapers, radio, television, the Internet, and court bulletin boards, in addition to holding press conferences or using other means to periodically publicize the dishonest judgment debtors. Therefore, information about local dishonest judgment debtors is publicly

[2] According to the Supreme People's Court, dishonest judgment debtors refer to those who fail to perform the obligations determined in an effective legal instrument and fall under any of the following circumstances: (1) Having the capability of performing obligations but refusing to perform the obligations determined in an effective legal instrument. (2) Obstructing or resisting enforcement by forged evidence, violence, threat, or any other methods. (3) Evading enforcement by fraudulent litigation or false arbitration, concealment or transfer of property, or any other method. (4) Violating the property reporting system. (5) Violating the Order on Restriction of Consumption. (6) Refusing to perform the enforcement reconciliation agreement without good reason.

available and deliberately made highly noticeable to individuals. Such information may draw the attention of local consumers and lead them to adjust their consumption behavior accordingly. Thus, the number of local dishonest judgment debtors provides a good opportunity to study how local people's consumption behavior responds to regional factors.

We use a unique credit card dataset from a leading commercial bank in China, which contains detailed records of individual consumption transactions for 432,088 individuals during the period from June 2013 to December 2015, as well as information on the individuals' personal characteristics, such as age, gender, marital status, education level, occupation, residential address, and property ownership. Based on the residential addresses of the card holders, we merge our consumption dataset with the dishonest judgment debtor data from the court in the same locality. Combining the monthly information on local dishonest judgment debtors with the individual consumption records within a court's jurisdiction, we can identify the effect of the number of local dishonest judgment debtors on individuals' consumption patterns. The panel structure of our data allows us to include individual fixed effects, ensuring that our findings are not driven by time-invariant differences in people's behavior that are correlated with the number of dishonest judgment debtors in the same court. Moreover, we include court and time fixed effects to control for unobserved variables.

We find that when a court publishes a list with a high number of dishonest judgment debtors, this is associated with a significant downward adjustment in consumption by the individuals residing in the court's jurisdiction (i.e., in the same local area) in a given month. Specifically, an increase of 1 percentage point in the number of local residents unable to comply with court orders results in a decrease in overall consumption by individuals of 10.39% in the month following this increase. Given that the number of local dishonest judgment debtors in a local court's jurisdiction is a noisy proxy for the local dishonest judgment debtors who come to the attention of consumers, these estimates should be viewed as lower (rather than upper) bounds of the actual effects of observing local dishonest judgment debtors.

We show that these effects are highly concentrated both temporally and spatially. In particular, the effects of the number of local dishonest judgment debtors on consumption materialize during the current month (i.e., the month when the list of debtors is published) and the following month, reach their lowest levels in the next following month, and then disappear after these three months. Thus, the number of local dishonest judgment debtors results in a sharp change in consumption that is not persistent. Similarly, as the spatial proximity of dishonest judgment debtors is widened from the local court's jurisdiction to the city level[3], the effects on consumption decline.

We analyze cross-sectional heterogeneity using our rich demographic information. We find that unmarried consumers, people with educational qualifications below the high school level, young people, and renters tend to reduce their spending in response to changes in the regional number of dishonest judgment debtors, indicating that these individuals are more sensitive and cautious about future spending than other consumers. In addition, we test the consumption response for different types of spending and find that people reduce spending on non-necessities by 7.62% when the number of local dishonest judgment debtors increases by 1%. However, there has no effect on the consumption of necessities.

Then, we explore how the number of local dishonest judgment debtors influences individual behavior, beginning with the role of attention (Barber and Odean, 2007; Gilbert et al., 2012; Sicherman et al., 2016). There is a positive correlation between searches using the Baidu index (i.e., the number of searches for a particular keyword or keywords, such as dishonest judgment debtors, in the most popular Chinese search engine) and the actual number of dishonest judgment debtors at the city level. This indicates that people are concerned about the increasing number of dishonest judgment debtors in the courts in their localities, and that they seek out information to adjust their consumption patterns in response.

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[3] Typically, basic court jurisdictions in China are based on the district level administration divisions, which are below the city level.

Why does paying attention to the local number of dishonest judgment debtors trigger adjustments in consumption? First, we investigate the potential predictive power of the number of local dishonest judgment debtors, and examine whether this number can be used to predict the future economic situation of the local area. We demonstrate that the number of dishonest judgment debtors in a particular region does not add predictive power to local economic conditions, labor income, and stock market returns when a set of common economic indicators is included in the model, indicating that the effect of dishonest judgment debtors is not the result of updated rational expectations about the economic situation. Second, we examine whether the number of dishonest judgment debtors in a locality affects consumer credit extension decisions and suppresses credit demand. We find that the number of dishonest judgment debtors has a significant and negative effect on the number of credit applications in the current and following two months. Specifically, a 1 standard deviation increase of the number of dishonest judgment debtors leads to a decrease in the number of credit card applications by 0.84 and 1.25 in the current and next months, respectively. In addition to credit demand, it is possible that local banks reduce their credit supply in response to an increasing number of dishonest judgment debtors. Therefore, we further examine whether the number of dishonest judgment debtors in a locality affects banks' credit supply, as represented by the approval rate of credit card applications. We find no evidence that banks change their credit supply policy in response to the number of dishonest judgment debtors.

Considering that the number of dishonest judgment debtors do not directly affect the wealth of local residents, our findings are unlikely to reflect changes in wealth or background risks, although we nevertheless test for this possibility. In addition, we find that the effect of regional dishonest judgment debtors on consumption is pronounced when we exclude consumers working in cyclical industries and non-tradable sectors, who are most exposed to local economic conditions. Our findings regarding the effect of the number of local dishonest judgment debtors on consumption remain stable across subsamples.

Furthermore, we conduct several robustness tests, including using alternative measures of consumption and dishonest judgments, and different samples, and our main results remain robust. First, we use the monthly number of purchases as an alternative measure of consumption and examine its response to the number of local dishonest judgment debtors. We find that a 1 percentage point increase in the number of local dishonest judgment debtors results in a statistically and economically significant decrease in consumer purchases of 8.17%. In addition, we use other local dishonest judgment debtor measures, such as the logarithm of the number of dishonest judgment debtors, and a variable ranging from one to four that indicates the dishonest judgment debtors measure falls within the quartile among observations from that court's jurisdiction over the sample period. Our results remain consistent for these alternative measures. When we exclude inactive account and outliers then rerun the main regression, the key coefficients remain significant. Furthermore, we conduct a placebo test to provide additional evidence that our findings do not reflect macroeconomic shocks or permanent local fixed effects that could potentially influence both dishonest judgment debtors and spending behavior.

Although the demonstrated relationship appears robust and economically significant, establishing direct causation is notoriously challenging. It is possible that a reverse causal effect might exist between the number of dishonest judgment debtors and the consumption of local residents. People who reduce their expenditure (i.e., for paying the debt) are less likely to have overdue repayments or bills, which reduces the number of court cases in which borrowers are required to repay their debts. To alleviate these concerns, we use an exogenous shock, namely, the official establishment and publication, from October 1, 2013, of the list of dishonest judgment debtors by the Supreme People's Court of the People's Republic of China. Using a difference-in-differences (DID) approach, we examine whether the change in the number of dishonest judgment debtors impacts local spending patterns before and after the shock. To avoid the effects of common time trends, we apply a variety of fixed effects at the individual and time levels to absorb the remaining unobserved time-invariant heterogeneity across individuals. By using this test, we verify the negative relationship between the number of local dishonest judgment debtors and individual consumption, with little concern of endogeneity.

Our paper is broadly related to the vast literature on peer and social multiplier effects (Glaeser, Sacerdote, and Scheinkman, 2003). Two notable mechanisms that affect consumers' consumption behavior are the "keeping up with the Joneses" and "catching up with the Joneses" effects (Abel, 1990; Gali, 1994), which encapsulate the fact that the average consumption of the reference group has a significant demonstration effect (Ravina, 2019). Using geographical proximity, Alvarez-Cuadrado et al. (2016) identify the reference group and find that if utility is defined to include consumption, one third of the weight is given to consumption. Different economic variables are documented in the literature that are related to peer effects, including education (Bobonis and Finan, 2009; Carrell, Sacerdote, and West, 2013), risky behaviors such as sex, crime, drugs, and smoking (Glaeser, Sacerdote, and Scheinkman, 1996; Card and Giuliano, 2013), workplace (Guryan, Kroft, and Notowidigdo, 2009; Mas and Moretti, 2009; Card et al., 2012), household savings and debt (Duflo and Saez, 2003; Breza, 2012; Beshears et al., 2015; Breza and Chandrasekhar, 2019), and portfolio choice and asset prices (Abel, 1990; Hong, Kubik, and Stein, 2005; Bursztyn, et al., 2014). By using geographic information to identify the reference group, our paper contributes to the literature by identifying a new regional component that affects consumption within the same group.

Our paper also contributes to the literature on the factors that influence consumption at the micro level. A large part of this literature focuses on individuals' consumption and savings responses to income uncertainty; for example, see Di Maggio et al. (2017), Agarwal, Pan, and Qian (2020), and Aydin (2022)[4]. We contribute to this strand of the literature by identifying personal consumption responses to changes in a regional factor.

Our findings contribute to understanding the role of experiences in shaping the

[4] For a complete review of the literature, please refer to Browning and Collado (2001) and Jappelli and Pistaferri (2010).

expectations and behavior of consumers. A growing literature records that the personal experience of economic outcomes, from global financial crises to individual-level job losses or stock returns, can shape individual beliefs and risk attitudes (Vissing-Jørgensen, 2003; Amromin and Sharp, 2009, 2014; Greenwood and Shleifer, 2014; Malmendier and Nagel, 2016; Roth and Wohlfart, 2019). Malmendier (2021) shows that experience effects help to understand belief formation and decision-making in a wide range of economic applications, including inflation, home purchase, mortgage choice, and consumption expenditure. A strand of the literature shows that significant heterogeneity exists across households in terms of how uncertain they are in their expectations regarding personal and macroeconomic outcomes (Landvoigt et al., 2014; Malmendier and Nagel, 2016; Das, Kuhnen, and Nagel, 2017). Moreover, studies show that local personal experiences shape beliefs about aggregate economic outcomes, for example, local house prices, house price volatility, and nationwide unemployment (Malmendier and Nagel, 2011, 2016; Malmendier, Nagel, and Yan, 2017; D'Acunto et al., 2019; Kuchler and Zafar, 2019). Our paper focus on the personal experience that is formed by local factors and records the effects of these local factors on individuals' decision-making process concerning their spending.

The remainder of this paper is structured as follows. In Section 2, we introduce the institutional background of dishonest judgment debtors and the publication of the list of these debtors in China. Section 3 describes the data and methodology. Section 4 presents our main results. Section 5 presents the source of endogeneity and the DID analysis, and Section 6 concludes the paper.

2. Institutional Background

The enforcement of court judgments has been a longstanding problem in China. The Supreme People's Court reports that between 2008 to 2012, over 70% of judgment debtors, whose cases were decided against them by courts across China, escaped, evaded, or violently resisted enforcement, with only 30% voluntarily complying with court judgments[5]. Many factors prevent a legally effective judgment from being enforced in a timely and effective manner, such as weak systems of property registration and social credit, low penalties for noncompliance, inadequate enforcement measures by the court, and incomplete enforcement procedures between the various administrations. By making enforcement difficult, courts lack the ability to effectively enforce the law, which impairs the rule of law and further damages the good faith that successful plaintiffs place in the legal system.

Chinese legislative bodies and judicial authorities have been working diligently to resolve this longstanding issue[6]. On July 16, 2013, the Supreme People's Court issued the "Several Provisions of the Supreme People's Court on Issuing the Information on the List of Dishonest Judgment Debtors" (2017 Amendment), which became effective on October 1, 2013. These provisions officially established the regulatory system of the list of dishonest judgment debtors, which is recognized as a powerful tool to address enforcement difficulties. From October 2013, people who, despite having the capacity to do so, fail to fulfill court orders and their obligations outlined in the effective legal documents, are included on a list of dishonest judgment debtors and subject to credit penalties and punishment. Courts at all levels are required to enter information about dishonest judgment debtors into the Supreme People's Court's dishonest judgment debtor database and to uniformly release the information through that database to the general public. In addition, courts at all levels are permitted to publish the list of dishonest judgment debtors through newspapers, radio, television, the Internet, and court bulletin boards, and may hold press conferences or use other methods to publicize the dishonest judgment debtors periodically. Therefore, information about local

[5] At a press conference on June 19, 2013, the Supreme People's Court announced several provisions regarding the publication of information on lists of dishonest persons. Details can be viewed at https://www.chinacourt.org/article/detail/2013/07/id/1038104.shtml.

[6] Efforts to resolve the issue of dishonest debtors can be traced back to Article 231 of the Chinese Civil Procedure Law, which was amended at the 30th session of the Standing Committee of the 10th National People's Congress on October 28, 2007. A people's court may adopt measures, or advise the unit concerned to do so, such as restricting the departure of the subject from the country, recording their failure to perform their obligations, or publishing information about their failure to comply with those obligations through the media if a person subject to enforcement fails to meet the obligations specified in a legal document. Therefore, it was decided by the legislative body that judgments could be enforced based on records within the credibility system and media publications.

dishonest judgment debtors is publicly available and deliberately made highly noticeable to individuals.

If an individual is included on the list, any extravagant consumption, that is, consumption that is not necessary for their daily life and work, will be strictly restricted, which is defined to include (1) taking an airplane, boarding a train on a soft berth, or traveling in a second-class berth or above; (2) engaging in high-level consumption activities at star hotels, nightclubs, golf courses, etc.; (3) purchasing real estate, or building, expanding, or luxuriously furnishing houses; (4) renting high-end office buildings, hotels, apartments, or other places for doing business; (5) purchasing vehicles not necessary for business operations; (6) traveling or taking a vacation; (7) sending their children to high-cost private schools; (8) purchasing insurance and financial products by paying high premiums; and (9) engaging in any other high consumption activities that are not necessary for living or working. The purpose of these measures is to ensure that individuals subject to enforcement face serious inconvenience in their daily lives. The measures place dishonest judgment debtors under pressure, thereby increasing the cost of their dishonesty, which deters them and others from dishonoring their debts, and encourages them to perform their obligations on a voluntary basis.

According to information published by the Supreme People’s Court, the Industrial and Commercial Bank of China has rejected 1.36 million loan or credit card applications made by dishonest judgment debtors, equivalent to approximately RMB9.9 billion. In total, 12.22 million people have been restricted from purchasing flight tickets, and 4.58 million people have been restricted from buying tickets for G-prefixed electric multiple units (“EMUs”) since July 2018[7].Due to the pressure imposed by these measures, 2.8 million dishonest judgment debtors have voluntarily fulfilled their obligations. From January to June 2018, RMB520 billion was paid back as a result of the enforcement

[7] The G-prefixed EMUs refers to high-speed trains with a speed of more than 250 kilometers per hour and a maximum speed of 300 kilometers per hour.

measures, which represents a growth of 44.06% from the previous year[8]. Thus, it is evident that the penalties imposed by the publication of the list of dishonest judgment debtors have had a significant and positive impact on debt repayments.

3. Data and Empirical Strategy

3.1. Data

We use three unique data sets for our analysis, including credit card spending data, with detailed transaction-level information and demographic information on card holders, the monthly number of dishonest judgment debtors at the court level in China, and credit card application data, including detailed application information and demographic information on the applicants.

3.1.1. Credit Card Spending Data

We obtain a unique proprietary data set from a leading commercial bank in China that accounts for 10% of China's credit card market, and covers all 31 provinces and municipalities. The data set contains information on the balances, spending, payments, and fees of individuals' monthly credit card statements for the entire population of the bank's credit cards from June 2013 to December 2015. The data set also contains the transaction information for each credit card transaction from June 2013 to December 2015, including transaction time, amount, merchant category code, and merchant name. In addition, it incorporates rich information on the demographic and socioeconomic characteristics of a random sample of credit card holders, including birth date, gender, ownership status, education level, marital status, number of dependents, employment status, name and industry of the employer, employer type (government, state-owned enterprise, or private sector), occupation, and income. The credit holder's residential address is our primary identifier to establish the link between consumers and the number of regional dishonest judgment debtors. We provide a detailed discussion of the

[8] "The Supreme People's Court: 2.8 million dishonest enforces have voluntarily fulfilled their obligations", published by china.com and accessed on July 27, 2018 at https://news.china.com/domesticgd/10000159/20180711/32664417.html.

merging process and sample in Section 3.2.

Our data set offers several advantages. First, our credit card data can capture a large proportion of the consumption response, as credit cards have become the primary method of payment for household consumption in China. According to the "Blue Book on the Development of China's Credit Card Industry" issued by the China Banking Association, by the end of 2015, China's total credit card transaction volume amounted to RMB21.7 trillion, equivalent to 31.5% of China's GDP in 2015. By the end of 2015, 432 million credit cards were used in China, and China's total credit card spending in 2014–2015 accounted for about 22.4% of total household consumption. Moreover, according to an investigation, about 73.5% of the respondents have more than two credit cards, suggesting that our credit card data capture a large proportion of the spending of the consumers in our sample[9].

Second, the richness of individual financial and demographic information facilitates an understanding of the heterogeneity of consumers' reactions to local dishonest judgment debtors. For example, we can track the demographics of individuals who hold credit cards, such as their residential address. This enables us to identify dishonest judgment debtors dealt with by a court in the same locality as the credit card holders, and analyze their impact on spending behavior in this area.

Finally, our administrative data set provides high-quality observations with low measurement errors. Compared with traditional surveys, recorded credit card transactions provide a more precise method of tracking individual behavior and the data set provides more reliable data on the demographic and socioeconomic characteristics of individual credit card holders. Every time a new banking relationship is established, the bank collects and verifies personal information.

[9] The survey results of "China Banking" magazine indicated that 31% of the interviewed customers owned two credit cards, 29.6% owned one credit card, and 20.6% owned three credit cards, suggesting that our credit card data covers a significant portion of consumer spending: https://kns.cnki.net/kcms2/article/abstract?v=3uoqIhG8C44YLTlOAiTRKibYlV5Vjs7ir5D84hng_y4D11vwp0rrtbOCFlaOnTfksmJp8MznsYRwFosrNumBDnJlrtuxdIXr&uniplatform=NZKPT

3.1.2. Dishonest Judgment Debtor Data

Dishonest judgment debtors are individuals or corporations capable of complying with a court order but who refuse to do so or resist enforcement and hence appear on the list published by Chinese courts. We focus on individuals who have been listed as dishonest judgment debtors. As noted, the list of dishonest judgment debtors is publicized to ensure that it is noticeable to individual consumers. Drawing consumers' attention to the local dishonest judgment debtors and their punishments may lead them to change their consumption habits to avoid any risk of sharing the same consequences.

For our analysis, we use the monthly number of dishonest judgment debtors from 2,413 courts at the district level in China from October 2013 to December 2015[10], which covers the sample period for our credit card consumption data (October 2013 to December 2015). The data include the number of dishonest judgment debtors publicly disclosed in a given month by the court. Panel A of Figure 1 displays how the average monthly raw number of dishonest judgment debtors is distributed across provinces during the time window that we analyze (October 2013 to December 2015), and indicates that there is a higher number of dishonest judgment debtors in the east than in the west of China. Panel B of Figure 1 shows that the average monthly raw number of dishonest judgment debtors has risen steadily. Although there are no significant seasonal patterns, the tendency to fail to fulfill debt obligations is slightly higher in the third and first quarters in a year than in other quarters.

*** insert Figure 1 about here ***

[10] In China, the People's Courts are organized into four levels: the basic, intermediate, high, and Supreme People's Court. In addition, there are special people's courts for military, railway, and water transportation. The basic people's courts in China are the county, municipal, autonomous county, and municipal district People's Courts. There are four types of intermediate people's courts: those established by provinces and autonomous regions, and those established by municipalities directly under the central government, as well as courts of cities under the jurisdiction of provinces and autonomous regions, and courts of autonomous prefectures. The higher-level people's courts comprise the higher people's courts of provinces, autonomous regions, and municipalities directly under the central government. There are approximately 3,100 courts at the district level in the whole country. We collect data on the number of dishonest judgment debtors from 2,804 courts across the country. After excluding courts with no dishonest judgment debtors during our study period and combining the court data with our consumption data, there are 2,471 courts at the district level in our sample.

3.1.3. Credit Card Application and Approval Data

The credit card application and approval data are sourced from the same bank as the spending data, and contain a total of 27,736,765 credit card application records from all 31 provinces and municipalities from January 2013 to July 2015. Local credit card applications are used to measure consumer credit demand, while credit supply is measured by how many people are approved for credit cards.

The application data set includes information regarding the application process for each credit card, including the application time and a rich set of demographic and socioeconomic characteristics of the applicants, including birth date, gender, ownership status, education level, marital status, number of dependents, employment status, name and industry of the employer, employer type (government, state-owned enterprise, or private sector), occupation, and income. We use the applicants' residential addresses to establish a link between applicants and dishonest judgment debtors in the region. Furthermore, our data set includes information on whether the applicants receive approval for credit cards.

3.1.4. Additional Data

We manually collect annual court-level population data from each city's yearbook. There are two types of population measures used in China, the resident population, which refers to the number of people who reside in a city, regardless of whether they are registered residents (*Hukou*), and the registered population, which refers to the people who have registered their permanent residence with the registration authority[11]. We use the resident population for our analysis because residents are more likely to be exposed to the publicity about dishonest judgment debtors by the local court than those not residing in the area.

In some of our analyses, we use a set of macroeconomic variables. Data on economic

[11] It is possible that members of the registration population live in a different area from where they registered their households, meaning that their current residences may differ from their place of registration.

conditions are not available at the court level. Therefore, we obtain quarterly GDP and yearly unemployment at the provincial level from the China National Bureau of Statistics. We include the disposable income of urban households per capita and the consumer price index at the province-month level, also sourced from the China National Bureau of Statistics, as control variables. In addition, we collect the monthly market value-weighted stock returns of China A-share from the China Stock Market & Accounting Research database (CSMAR)[12].

3.2. Merged Final Sample and Summary Statistics

The credit card spending data in our database are drawn from a random sample of all accounts in the bank with demographics and financial characteristics[13]. For our analysis, we restrict our main sample to active consumers (i.e., we exclude inactive consumers who have no transactions during our sample period). We also exclude consumers younger than 18 years of age. Finally, we are left with 432,088 individuals. Following Agarwal and Qian (2014, 2017), we aggregate the credit card spending data at the individual-month level. Monthly credit card spending is computed by adding monthly spending for each individual. We code observations of flow variables as 0 if the consumer has no corresponding transactions in the given month.

We match a card holder's residential address from the credit card data with the dishonest judgment debtor data (i.e., the name of the court and its jurisdiction). A summary of the statistics of our sample can be found in Table 1. In Panel A, we present the summary statistics of consumer demographics and spending. For all consumers in our sample (N = 432,088), the average age is 37.93 years, 44.23% of the sample are women, 72.68% are married, 17.13% are high school or below education background, 89.2% own a home, and the average monthly consumption is 3,619 yuan (about US$506.6).

[12] CSMAR is a comprehensive research-oriented database focused on financial and economic data in China, offering data on China's stock markets and the financial statements of Chinese listed companies.
[13] According to our comparison of the random sample of credit card holders with the full sample, the random sample has similar observational characteristics to the rest of the full sample. In other words, it is a representative sample of the bank's credit card user population.

As shown in Table 1, Panel B, the monthly average number of local dishonest judgment debtors at the court level is 38.24. We scale the monthly number of dishonest judgment debtors by dividing the number by the previous year-end number of the resident population in the same court. This scaling incorporates the fact that consumers living in courts with a large resident population are exposed to many financially sound consumers as well as to many consumers who are in default. We trim the monthly measure of dishonest judgment debtors to the 99th percentile to reduce the impact of outliers. To make the coefficients in our regressions easier to interpret, we multiply the resulting monthly measure of dishonest judgment debtors by 100. We combine this monthly measure of dishonest judgment debtors with our credit card spending data set based on court identifiers (names). This results in a measure of dishonest judgment debtors that ranges between 0 and 1.6, with an average of 0.007 at the court level. This indicates that consumers in our data set are exposed to 0.007% of dishonest judgment debtors each month.

This data set contains information on the number of credit card applicants in 2,457 courts located in 31 provinces and municipalities between January 2013 and July 2015. According to Table 1, Panel C, the mean number of monthly applicants is 264.74, the mean number of monthly approved applicants is 71.97, and the monthly average approval rate is about 27.19%.

Additional economic data are incorporated into our analysis, including the province's yearly local unemployment rate, the logarithm of the province's quarterly local GDP per capita, as well as the market value-weighted stock returns of China A-shares as a monthly indicator of the market value of stock returns, all of which are based on time and location. Furthermore, we construct control variables using the monthly logarithm of the disposable income of urban households per capita and the monthly consumer price index at the provincial level. Table 1, Panel D, provides a detailed description of the variables that we use.

*** insert Table 1 about here ***

To examine whether dishonest judgment debtors differ over time and across courts, and whether regional dishonest judgment debtors are persistent, we estimate the scaled number of dishonest judgment debtors using different sets of fixed effects and lags. Based on Table A1, the R-squared for the scaled number of dishonest judgment debtors regressed with only time fixed effects is 2% (column 1). The R-squared increases to 17.8% (column 2) when court fixed effects are included in the specification. The findings suggest that the variation in the number of dishonest judgment debtors is due to permanent differences between courts, which also indicates the explanatory power of court fixed effects. Furthermore, when the lagged measure is added to our regression, the R-squared increases to 22.4% (column 7).

3.3. Empirical Specification

To evaluate the consumption response to the local dishonest judgment debtors in the same court, we estimate the following fixed-effects specification using ordinary least squares (OLS):

$$\log(\mathrm{con}_{i,j,t}) = \alpha_0 + \alpha_t \mathrm{DJD}_{j,t} + Z_{j,t} + \mathrm{individual}_i + \mathrm{court}_j + \mathrm{time}_t + \epsilon_{i,j,t} \tag{1}$$

where $\log(\mathrm{con}_{i,j,t})$ denotes the logarithm of (1 plus) consumption (in RMB) for individual *i* living in the locality of court *j* at time *t*. $\mathrm{DJD}_{j,t}$ measures the scaled monthly number of dishonest judgment debtors in court *j* at time *t*. Our main parameter of interest is the marginal effect of DJD. The vector $Z_{j,t}$ includes a set of control variables, such as last quarter's seasonally adjusted log of GDP per capita and last year's unemployment rate at the provincial level, the seasonally adjusted log of the disposable income of urban households per capita, and the consumer price index (based on the same month last year) at the province-month level. We include individual fixed effects to control for unobserved time-invariant differences in consumption behavior across individuals that could be correlated with persistent differences in exposure to the local number of dishonest judgment debtors. We control for time fixed effects to account for common macroeconomic conditions. We also include court fixed effects to control for constant differences in each court. Hence, we identify the effect of the local number of dishonest judgment debtors from the within-consumer variation in spending activity over time and the cross-sectional variation in exposure to the local number of dishonest judgment debtors. Throughout, standard errors are clustered at the individual and year-month level.

4. Main Results

4.1. Does the Number of Local Dishonest Judgment Debtors Predict Changes in Consumption?

In this section, we test our hypothesis regarding the relationship between consumption and the number of local dishonest judgment debtors. We estimate equation (1) and present the results in Table 2. It is apparent that people exposed to a high number of local dishonest judgment debtors significantly reduce their consumption in the current period and the next period. Specifically, an increase of 1 percentage point in the share of local people who fail to comply with the court's order results in a decrease of 9.62 percentage points in individuals' monthly consumption in the current month (column 1). More significantly, in the following month, a 1 percentage point increase in the number of dishonest judgment debtors among locals causes the consumption of individuals in the region of the same court to fall by 10.39% (column 2), and the coefficient for the second lag of number of local dishonest judgment debtors becomes small and less significant (column 3). In contrast, the coefficient for the third lag of the number of local dishonest judgment debtors is economically small and statistically indistinguishable from 0 (column 4). Additionally, in columns (4) and (7), we include dishonest judgment debtor estimates for the current month and the previous three months, and show that only the current month and the previous two months have a significant effect on consumption. Given these findings, it appears that the impact of dishonest judgment debtors on spending is immediate but not persistent, and that the contemporary local measure of dishonest judgment debtors is insufficient to capture the lagged effects of earlier dishonest judgment debtors.

In our analysis, we use the scaled number of local dishonest judgment debtors in a consumer's resident court as our independent variable, which is a noisy proxy for the actual number of dishonest judgment debtors that the consumer has observed. Therefore, our estimates can be interpreted as a lower bound estimate of the effect of noticing local dishonest judgment debtors on consumer spending.

Overall, our results indicate that in response to the number of local dishonest judgment debtors, consumption decreases in the current month and the following month, reaches its lowest level in the next following month, and then disappears after these three months. Aydin (2022) observes that when the credit limit is increased, the marginal propensity to consume in the following period increases and becomes more significant than when the credit limit is lower. It takes time for consumers to realize a shock, form a new expectation about their income or risk, and adjust their consumption behavior accordingly. As a result of the detailed arrangements for exposure of dishonest judgment debtors, the basic courts must provide a list of such debtors to the supreme court, which then compiles the database so that all courts at all levels can access it. It takes time for the list to be published after verifying the dishonesty of the debtors. Given this lag, we focus on consumer spending in the next month after the publication of the list in the following analysis.

*** insert Table 2 about here ***

4.2. Spatial Proximity

Testing the spatial proximity of dishonest judgment debtors improves understanding of how regions at different geographical scales (e.g., local vs. regional) react to a change in the number of local dishonest judgment debtors. In addition, broadening the spatial proximity of dishonest judgment debtors from the court to the city facilitates identification of the range of their influence. The number of dishonest judgment debtors at the city level is aggregated and divided by the number of residents in the city in the previous calendar year. City fixed effects are included, and standard errors are clustered at the individual and year-month level. Table 3 presents the results. Although the number of city-level dishonest judgment debtors has a statistically significant effect on individuals' consumption in the city in both the current month and the following two months, the effect is smaller than the court-level effect. Consequently, the number of dishonest judgment debtors in the local area of a court affects individuals' consumption more profoundly than the number of dishonest judgment debtors throughout a wider geographical area.

*** insert Table 3 about here ***

4.3. Cross-Sectional Heterogeneity

According to the above results, dishonest judgment debtors in the local area have a statistically and economically significant impact on consumers' spending. By using detailed information about consumer characteristics and spending type, we further investigate the heterogeneity of this impact.

4.3.1. Heterogeneous Responses Across Consumers: Who Responds More?

By utilizing the detailed consumer demographic information in our data set, we can assess the heterogeneity of consumer characteristics to understand their spending responses. We hypothesize that if there is a change in consumption levels due to the number of dishonest judgment debtors, the effect will be pronounced among individuals whose characteristics make them susceptible to the number of such debtors at the local level. For example, those who are more cautious about their future spending behavior or who plan their consumption carefully are more likely to change their consumption behavior than consumers who are less cautious or plan less carefully. We estimate equation (1) by integrating the scaled number of dishonest judgment debtors with indicators based on a consumer's marital status, gender, education level, age, and homeownership status.

As shown by Table 4, the spending of married consumers declines less than the spending of married consumers, in response to an increase of number of local dishonest judgment debtors (column 1). Males also decline less than the women (column 2). People with lower educational qualifications (below the high school level) decrease their consumption more than those with higher degrees. Specifically, an increase in the scaled number of dishonest judgment debtors by 1 percentage point is associated with a decrease in consumption by less educated individuals of 14.26 percentage points in the next month (column 3). When the scaled number of dishonest judgment debtors increases by 1 percentage point, young people (below the 35 year old) decrease their consumption by 26.22 percentage points (column 4) and the house owners are less sensitive to the increase of dishonest judgment debtors than the renters.(column 5).

*** insert Table 4 about here ***

4.3.2. Heterogeneous Responses Across Consumption Types

Next, we examine the heterogeneity associated with the type of consumption. Taking advantage of the detailed information provided by merchant category codes in our consumption data set, we group transactions into necessities and non-necessities. Consumption of necessities includes spending on groceries, dining, and transportation. Non-necessities include entertainment, apparel, and travel.

In Table 5, we report the results from re-estimating equation (1) using these two subsamples. We find that people become cautious in relation to their spending on discretionary consumption as the number of local dishonest judgment debtors increases. They reduce their spending on non-necessities by 7.62% in the next period when the number of local dishonest judgment debtors increases by 1% (column 2), which suggests precautionary motives as people reduce their discretionary consumption to ensure future spending. However, this effect is not significant for the consumption of necessities, as shown in column 1.

*** insert Table 5 about here ***

4.4. Do Consumers Care About Local Dishonest Judgment Debtors

In the previous section, we establish that exposure to a high number of local dishonest judgment debtors leads consumers to reduce their spending and that these results are not driven by omitted variables, such as poor macroeconomic conditions. In this section, we examine consumers' attention to dishonest judgment debtors. How does a consumer find information about dishonest judgment debtors and their punishments? The literature establishes that consumers are increasingly aware of macro-level variables, such as income growth, stock market returns, inflation, and unemployment at different regional levels and how these variables affect household economic behavior (Souleles, 2004; Malmendier and Nagel, 2016; Ben-David et al., 2018; Das, Kuhnen, and Nagel, 2020;). In addition, some researchers analyze Google indexes of specific events, such as bankruptcy and specified public stock numbers or names, to determine how attention affects investment behavior (Da et al., 2011; Laudenbach, 2021).

Individuals concerned about dishonest judgment debtors in their local area will search for more information on the Internet. According to the 37th statistic report on China's international development from the China Internet Network Information Center (CNNIC), the number of search engine users in China reached 566 million at the end of 2015, representing a utilization rate of 82.3%[14]. Search engines are the most commonly used Internet application, and their utilization rate is second only to instant messaging. In China, the most popular search engine is Baidu, which is an important source of information for the Chinese population. The Baidu index combines information about particular words from multiple sources such as the number of searches and the reporting of the media. Using the Baidu index, it is possible to measure the attention that consumers pay to a particular keyword at a specific geographical level and point in time.

To measure the demand for information about dishonest judgment debtors, we use monthly statistics from the Baidu index for the term "dishonest judgment debtors" at

[14] This statistic comes from CNNIC's 37th Statistic Report on China's International Development, which can be accessed at http://www.cnnic.net.cn/hlwfzyj/hlwxzbg/201601/P020160122469130059846.pdf.

the city level during the sample period. Furthermore, we divide it by the previous calendar year's residential population to eliminate any concerns regarding the existence of a positive relationship between regional residents and dishonest judgment debtors. All numbers are standardized between 0 and 100.

Figure 2 illustrates the relationship between the Baidu search index and the actual number of dishonest judgment debtors using a binned scatter plot and linear fit. As indicated by Figure 2 panel A, there is a significant and positive correlation between Baidu searches and the actual number of dishonest judgment debtors at the city level, indicating that people are concerned about the increasing number of local dishonest judgment debtors. In panel B we show the same plot after partialing out city fixed effect. In general, these results suggest that information about local dishonest judgment debtors reaches the local community quickly through the Internet, the most widespread medium for disseminating information about local dishonest judgment debtors. Therefore, individuals may adjust their consumption behavior in response to the number of local dishonest judgment debtors after receiving the relevant information.

*** insert Figure 2 about here ***

4.5. How Do Local Dishonest Judgment Debtors Affect Consumption?

Internet searches seem to play an important role in drawing consumers' attention to dishonest judgment debtors, and the number of such debtors has a greater impact on consumption when consumers' awareness of the existence of debtors is raised. However, the question is, through what channels is consumers behavior affected by dishonest judgment debtors?

This subsection examines in detail whether the number of local dishonest judgment debtors triggers an active downward adjustment of consumption through (i) pessimistic income expectations or high perceived background risk; (ii) reduced credit demand of consumers; or (iii) a reduction in credit supply by banks.

4.5.1. Are Local Dishonest Judgment Debtors Informative?

It is possible that consumers may update their expectations about their disposable income or risk background if they consider that the number of regional dishonest judgment debtors is indicative of the region's future economic development and hence their own personal income, leading them to alter their consumption behavior. In addition, individuals who are unable to comply with a court order may suffer from personal financial difficulties due to an adverse event that occurred much earlier than the court order. Therefore, we examine whether the number of local dishonest judgment debtors can predict the future state of the economy and personal income in the local area to explore the potential predictive ability of the number of local dishonest judgment debtors. Following Korniotis and Kumar (2013), we test the informative content of the number of dishonest judgment debtors using the following model:

$$y_{j,t} = \beta DJD_{j,t-k} + time_t + geography_j + \epsilon_{t,i,j} \quad (2)$$

where the dependent variable $y_{j,t}$ represents several variables related to economic conditions, such as GDP and unemployment rates. Based on the limitations of the data, the temporal level t of the dependent variables has different meanings, including year and quarter. Geographically, level j refers to the country or province of the dependent variable. As the primary independent variable, dishonest judgment debtors are scaled according to geography and time. To better understand the dynamic effect of different time horizons on economic conditions, we incorporate $k = 1$ to $k = 6$ periods of the number of local dishonest judgment debtors into our regression. Geographical and time fixed effects are controlled for in accordance with their aggregation levels, except for the regression at the country level.

As noted above, we have various dependent variables. Economic development is described by the log of GDP per capita obtained from the China National Bureau of Statistics at the provincial and quarter levels. Personal income volatility is measured by the yearly unemployment rate at the provincial level, also sourced from the China National Bureau of Statistics. We collect monthly market value-weighted stock returns for China A-shares from CSMAR. We aggregate the raw numbers of local dishonest judgment debtors differently according to their spatial-temporal levels and then scale them according to local residential levels.

As shown in Table 6, all of the coefficients that we estimate using the different specifications are not statistically or economically significant, suggesting that the number of dishonest judgment debtors does not have enough informative content to predict the log of GDP per capita for the province (column 1), the unemployment rate for the province (column 2), or the returns on public company stocks at the country level (column 3). These findings indicate that changes in consumption that result from the number of local dishonest judgment debtors are not driven by rational adjustments to expectations about the development of the regional economy, personal income risk, or stock returns, and that an increase in the number of dishonest judgment debtors is not an indication of an actual worsening of economic conditions in the future.

*** insert Table 6 about here ***

4.5.2. Do Local Dishonest Judgment Debtors Affect Credit Demand?

The policy of disclosing information about dishonest judgment debtors and ensuring that the information is transparent and widely accessible means that the policy serves as a means of punishment of such debtors and provides strong incentives for local residents to fulfill their debt obligations on time to avoid being listed. As a result of inclusion on the publicly announced list of dishonest judgment debtors, not only will a person suffer damage to their reputation but they will also be subjected to extensive restrictions on consumption, which are likely to cause extreme inconvenience in their daily lives and work, such as restrictions on taking an airplane, boarding a train on a soft berth, or traveling in a second-class berth or higher. Given these consequences of being listed as dishonest, people are likely to evaluate their solvency discreetly and carefully to avoid being penalized. Thus, there is a possibility that a high number of dishonest judgment debtors could increase people's prudence regarding their demand for credit.

In the face of high numbers of dishonest judgment debtors, local consumers may be unwilling to apply for credit extension or new credit cards, which may constrain the available credit line for local consumers and decrease their consumption. Therefore, we wish to clarify whether a high level of local dishonest judgment debtors suppresses consumption through restraining credit demand. To measure the demand for new credit in a locality, we use the number of credit card applicants and the following specifications to assess how the number of dishonest judgment debtors affects the number of credit card applicants:

$$\mathrm{app}_{j,t} = \alpha_0 + \alpha_1 \mathrm{DJD}_{j,t} + \mathrm{court}_j + \mathrm{time}_t + \epsilon_{j,t} \tag{3}$$

where the dependent variable $\mathrm{app}_{j,t}$ represents the number of credit card applicants in court *j* at time *t*. $\mathrm{DJD}_{j,t}$ measures the origin number (without scaling based on local populations) of dishonest judgment debtors in court j at time t. Our coefficient of interest is α_1, which explains the effect of dishonest judgment debtors on application willingness. We include court fixed effects to control for the unobserved time-invariant difference in each court and time fixed effects to capture the systematic difference between observed time units. Throughout, standard errors are clustered at the court level.

The results for the influence of dishonest judgment debtors on credit demand are shown in Table 7, which indicates that the coefficients on the local number of dishonest judgment debtors in the current and following periods are negative and economically significant. This suggests that a high number of local dishonest judgment debtors results in a decrease in local credit demand in the localities of the courts. When dishonest judgment debtors increase by 1 deviation, credit card applicants decrease by 0.84 in the current month (column 1) and 1.25 in the next month (column 2). Based on the results obtained after two months (column 3), it appears that this effect is less significant and becoming small and then fades within a short period[15]. The impact of dishonest judgment debtors on credit card applications is greater in the next month than in the

[15] We find no effect when we add further lags of the dishonest judgment debtors measure in unreported regressions.

current month, and the effect disappears after three months, which is consistent with our main findings. It is evident from these findings that the announcement of a high number of dishonest judgment debtors causes a reduction in consumers' spending as a result of local people becoming reluctant to apply for new credit.

4.5.3. Do Local Dishonest Judgment Debtors Affect Credit Supply?

In addition to credit demand, dishonest debtors may affect banks' credit supply at the local level. In making lending decisions, the risk of default is an important factor that banks consider. In areas with a high number of dishonest judgment debtors, banks may perceive greater credit risk than in areas with a low number of dishonest judgment debtors. Therefore, banks may tighten their credit policies, by raising the interest rates offered on credit cards, requiring more collateral, or imposing stricter criteria for lending than in situations with fewer dishonest judgment debtors.

To examine whether local banks change their credit supply in response to the number of dishonest judgment debtors, we replace the dependent variable $app_{j,t}$ in equation (3) with the number of credit cards approved to represent the banks' credit supply, and re-estimate equation (3).

*** insert Table 7 about here ***

As shown in Table 7, the coefficients in columns 4-6 are not statistically or economically significant. Therefore, the number of local dishonest judgment debtors has no significant impact on credit supply during our period of analysis. Consequently, we are able to exclude the influence of credit supply on changes in consumption behavior.

Overall, our findings show that changes in consumption are not driven by rational adjustments to expectations about the future regional economy. Furthermore, we find that the disclosure of the number of local dishonest judgment debtors influences consumer behavior through the mechanism of altering credit demand rather than credit supply. This occurs because the disclosure policy increases the cautiousness of individuals in the local community in making credit extension decisions, which can then alter their credit demand and result in subsequent changes in their consumption habits.

4.6. Robustness Tests

4.6.1. Changes in Background Risks

It is possible that background risks, such as risks associated with one's occupation, may influence personal consumption. Based on the above tests, it is evident that the effect of the number of dishonest judgment debtors in the local region is geographically and temporally concentrated. Thus, our findings are unlikely to be influenced by unobserved factors, such as a person's background risks. To verify these results, we perform additional tests.

First, we examine the impact of the number of local dishonest judgment debtors within subsamples of individuals whose labor income is less sensitive to changes in the local economy than other subsamples of individuals. Table 8, column 1, shows the results of excluding consumers working in cyclical industries that are sensitive to economic conditions. The business cycle significantly affects people working in manufacturing, finance, tourism, transportation, warehousing, and logistics, whereas those working in other fields, such as education and health, will be less affected (Takhtamanova and Sierminska, 2016). Therefore, we examine the effects of dishonest judgment debtors on consumption using the sample without individuals working in cyclical industries. Having excluded the cyclical sample, we find that the effect of local dishonest judgment debtors on consumption remains significant. If there is a 1% increase in the number of local dishonest judgment debtors, those who live in the same court region will reduce their consumption by 10.09%.

Second, as shown in column 2 of Table 8, we exclude individuals in non-tradable industries, such as health, social welfare, and justice, which are likely to be influenced by changes in local economic conditions (Mian and Sufi, 2014). Then, we re-estimate equation (1) to test the impact of local dishonest judgment debtors on consumption. According to the result, a 1% increase in the number of local dishonest judgment debtors is associated with an 9.79% reduction in individual consumption after excluding individuals working in non-traded sectors. This result is almost identical to that of the baseline model.

Overall, these subsample tests provide us with solid evidence that our findings are not impacted by individual background risks resulting from fluctuations in regional economic conditions.

*** insert Table 8 about here ***

4.6.2. Alternative Measure of Consumption

In addition to examining the response of spending amounts to the number of local dishonest judgment debtors, we test the robustness of our findings by adopting the number of purchases as an alternative measure of consumption. We aggregate the number of purchases at the consumer-month level and then repeat our baseline analysis in Table 2 using purchases as the dependent variable. As Table 9 shows, consistent with the baseline results, the coefficients of the lagged number of local dishonest judgment debtors are statistically and economically significant. An increase of 1 percentage point in the number of local dishonest judgment debtors is associated with a decrease of 8.17 percentage points in monthly consumption by consumers (column 2).

*** insert Table 9 about here ***

4.6.3. Alternative Measures of Dishonest Judgment Debtors

As a further robustness test of our findings, we use different dishonest judgment debtor measures. In Table 10, we substitute our original measure of dishonest judgment debtors (the raw number of dishonest judgment debtors in a court area divided by the previous year's residential population) with other measures of dishonest judgment debtors, such as taking the logarithm of the number of dishonest judgment debtors and defining a variable between one and four that indicates in which quartile the dishonest judgment debtors measure falls within the sample period . When we use the logarithm of dishonest judgment debtors in the specification, the effects on consumption remain significant. However, they have a relatively smaller coefficient than the baseline. This is probably because the logarithm of the number of dishonest judgment debtors disregards the positive relationship between the number of local residents and the number of dishonest judgment debtors in the locality. In the case of the measures using the quartile indicating variable, we see similar results. Overall, these estimates based on alternative dishonest judgment debtor measures are typically noisier than our baseline results. The reason for this is that we do not adjust the number of dishonest judgment debtors for differences in the local number of households. Nevertheless, the results are consistent with the findings of our baseline model.

*** insert Table 10 about here ***

4.6.4. Placebo Analysis

To control for unobservable variables that may influence our findings, we include time, court, and individual fixed effects in our baseline model. Concerns may arise regarding whether our model contains sufficient variables to describe the impact of local dishonest judgment debtors on consumption. This section performs a placebo analysis for our study.

The first placebo test is designed to address the concern that time fixed effects do not adequately account for macroeconomic fluctuations. For each court-month, we replace the measure of local dishonest judgment debtors for the region associated with that court with a measure that is randomly drawn (with replacement) from all measures of local dishonest judgment debtors across all courts in the same month. Then, we re-estimate the baseline model using this artificial data set. As shown in Table 11, column 1, the impact of local dishonest judgment debtors on individual consumption is not statistically significant. This suggests that individual consumption is not affected by macroeconomic fluctuations. Second, we design a placebo test to ensure that court fixed effects fully control for the effect of permanent differences across courts. For each court-month, we replace the baseline measure of local dishonest judgment debtors with one that is randomly drawn (with replacement) from all measures of local dishonest judgment debtors over the sample period for that court. Using this specially constructed data set, we re-estimate the baseline model. As shown in column 2 of Table 11, the coefficient obtained from the regression is not significant and much smaller than that obtained from our baseline model. These results provide additional evidence that our findings do not reflect macroeconomic shocks or permanent local fixed effects that could be driving both the number of dishonest judgment debtors and consumers' spending behavior.

*** insert Table 11 about here ***

4.6.5. Removing Inactive Accounts and Outliers

As a further robustness test, we first exclude the inactive accounts in our sample. In columns 1 to 3 of Table 12, we keep consumers whose average monthly spending is non-zero for more than 6 months, 9 months, and 12 months and then estimate the consumption response for these consumers, respectively. All the results are robustness after removing the inactive account. Second, we remove the courts that experience an extreme number of dishonest judgment debtors during the sample period to eliminate the influence of outliers. As shown in, column 4, we find that consumption decreases by 10.11% when the number of local dishonest judgment debtors increases by 1%, and this effect is statistically and economically significant. Next, we estimate the consumption response in column 5 after remove the consumers with consumption above the 99th percentile. Again, individuals' consumption decreases by 10.19% when the number of local dishonest judgment debtors increases by 1%. Overall, our basic findings remain robust after removing outliers.

*** insert Table 12 about here ***

5. Sources of Endogeneity and Identification

5.1. Sources of Endogeneity

According to our findings, the number of local dishonest judgment debtors directly and negatively impacts the consumption behavior of individuals living in the region covered by the same court. However, this result raises questions regarding endogeneity if it is interpreted as causal evidence.

First, other variables may be omitted from different dimensions, such as personal financial conditions, the macroeconomic situation, and constant differences within each court. We alleviate this concern by controlling for individual, time, and court fixed effects in our baseline model. In other words, by taking into account all of these variables at the same level, we investigate how the change in the number of local dishonest judgment debtors impacts the spending behavior of consumers living in the region covered by the same court. A second concern is that there could be a reverse causal effect between the number of local dishonest judgment debtors and the consumption of local residents. In particular, when people decide to reduce their spending, they are more likely to be able to reimburse banks or other personal lenders, which would reduce the number of court proceedings requiring borrowers to repay any arrears. If this is the case, the change in personal spending behavior of those living in the same court will result in a change in the number of individuals who fail to fulfill the order within that court.

5.2. Difference-in-Differences Analysis

To better isolate the effect of local dishonest judgment debtors on consumer spending, we conduct a DID analysis by exploiting the spending changes of consumers after the first release of the list of dishonest judgment debtors. Using this DID analysis can mitigate concerns about omitted variables and also effectively remove the impact of concurrent macroeconomic shocks that may affect consumer spending.

On July 19, 2013, the Supreme People’s Court of the People’s Republic of China issued “Several Provisions on Publishing Information on the List of Dishonest Judgment

Debtors," which came into effect on October 1, 2013. Subsequently, the names and details of individuals capable of fulfilling the court's orders but who fail to comply with them, are published, through the Internet and other media.

As mentioned above, our identification strategy takes advantage of the exogenous shock involving changes in government regulations leading to the publication of the list of dishonest judgment debtors and associated penalties. It examines how individual consumption changes in response to exogenous variations in the publication of a list of dishonest judgment debtors. The DID methodology is ideally suited to our study for the following reasons. First, it addresses the issue of reverse causality by taking into account the shock involving the published list of dishonest judgment debtors. Second, the administrative decision to expose and the time of exposure and coercive control of dishonest judgment debtors seem to be exogenous to the debtors' unobservable characteristics. Therefore, we treat the regulatory change imposed by the government as an exogenous shock.

As a result of the regulation formulated by the supreme courts, which creates a new mandatory requirement for basic courts to publish the number of local dishonest judgment debtors, the number of local dishonest judgment debtors tends to increase. Furthermore, considering the lag between the implementation of the policy and the publication of the number of dishonest debtors, we can assume that the number of dishonest people is stable in October 2013 when the government regulation came into effect[16]. Using the number of local dishonest judgment debtors in October 2013, we quantify the degree of the shock to the number of local dishonest judgment debtors, which is scaled by dividing the previous calendar year's number of local dishonest judgment debtors in our analysis. We obtain individuals' consumption from June 2013 to September 2013 and append them to our baseline sample. Our time window for analysis is determined by extending the observation period to four periods prior to the

[16] According to the "Several Provisions on Publishing Information on the List of Dishonest Judgment Debtors," basic courts are first required to notify the supreme court of the number of dishonest judgment debtors within their jurisdiction, and then choose the appropriate method of publishing the list and exposing the debtors, which takes time.

shock constituted by the publication of the list of dishonest judgment debtors and six periods following the shock.

We conduct our DID analysis using the model of Bai and Jia (2010) to examine the effect on consumption before and after the compulsory exposure of the list of dishonest judgment debtors:

$$\begin{aligned}\log\_con_{\mathrm{i,j,t}} &= \alpha_0 + \alpha_1 \ln\left(\frac{\text{raw DJD}_{\mathrm{j,2013.10}}}{Pop_{j,2012}}\right) \times \text{post}_t \\ &\quad + \alpha_2 \ln\left(Pop_{j,2012}\right) \times \text{post}_t + \text{individual}_{\mathrm{i}} + \text{time}_{\mathrm{t}} + \epsilon_{\mathrm{i,j,t}} \\ &= \beta_0 + \beta_1 \ln\left(\text{DJD}_{\mathrm{j,2013.10}}\right) \times \text{post}_t + \beta_2 \ln\left(Pop_{j,2012}\right) \times \text{post}_t + \\ &\quad + \text{individual}_{\mathrm{i}} + \text{time}_{\mathrm{t}} + \epsilon_{\mathrm{i,j,t}} \qquad (4)\end{aligned}$$

The dummy variable post_t is 0 for all months before October 2013 and 1 for the month after October 2013. $\log\_con_{\mathrm{i,j,t}}$ is the logarithm of the consumption of individual *i* living in court *j* at time *t*. $\ln\left(\text{DJD}_{\mathrm{j,2013.10}}\right)$ is the logarithm of the number of local dishonest judgment debtors in court *j* in October 2013, which is designed to measure the magnitude of the effect of the government regulation. $\ln\left(Pop_{j,2012}\right)$ is the logarithm of the population in court *j*. Individual $_{\mathrm{i}}$ and time $_{\mathrm{t}}$ denote individual and time fixed effects to control for all time-invariant differences between people and changes over time that affect all individuals similarly. Standard errors are clustered at the court level.

The results are presented in Table 13. The key coefficient of the interaction term $\ln\left(\text{DJD}_{\mathrm{j,2013.10}}\right) \times \text{post}_t$ is negative and statistically significant at the 1% level, as shown in column 1. It indicates that the shock of the government regulation on the list of dishonest judgment debtors from October 2013 causes a change in individuals' spending behavior in the opposite direction that is proportional to the magnitude of the exogenous shock to the published number of dishonest judgment debtors. Column 2 repeats the analysis in column 1, but with controlling for the logarithm of the resident population in the same court's jurisdiction to determine whether the result remains robust. As in column 2, the estimated coefficient is negative statistically and economically significant with a similar magnitude to the result in column 1. suggesting that our DID inference is robust to differences in specifications.

*** insert Table 13 about here ***

In addition, we examine the dynamic effect of spending responses using the following model:

$$\log\_con_{i,j,t} = \alpha + \Sigma\, \mu_t \ln\left(\mathrm{DJD}_{\mathrm{j,2013.10}}\right) \times \mathrm{post}_t + \Sigma\, \nu_t \ln\left(Pop_{j,2012}\right) \times \mathrm{post}_t + \mathrm{individual}_\mathrm{i} + \mathrm{time}_\mathrm{t} + \epsilon_{\mathrm{i,j,t}} \quad (5)$$

where September 2013 is retained in the analysis as a comparison. The results are shown in Figure 3, where the solid line connects the estimates, and the dashed lines indicate the 95% confidence intervals with standard errors clustered at the court level. During the time before the shock, the impact of dishonest judgment debtors on consumption is around 0 and not statistically significant. However, the coefficients for the months after the shock are negative and significant. The figure shows that there are no significant differences in the pre-trends for the courts with high and low dishonest judgment debtors, while the negative impact of dishonest judgment debtors on individual consumption occurs after October 2013 when the government regulation came into effect. The magnitudes of the impacts are around -0.015 from October 2013 to March 2014, similar to our DID analysis.

*** insert Figure 3 about here ***

In summary, we address endogeneity concerns by defining the magnitude of the shock and using a DID analysis with the same individuals as the baseline sample. The results confirm our baseline results, which suggest that the number of local dishonest judgment debtors has a negative effect on personal spending behavior.

6. Conclusion

Using a representative sample of consumer credit card transaction data in China, this paper studies the effect of the regional number of dishonest judgment debtors on individual consumption behavior. Our findings suggest that an increase in the number of local dishonest judgment debtors leads to an exogenous and significant reduction in consumption in the short term. Using geographical information to identify consumers in the same court jurisdiction, who are close to being randomly chosen, and the forced exposure arrangement of dishonest judgment debtors, which is also endogenous, allows us to capture the power of regional factors on individual consumption behavior without endogeneity.

We document that consumers reduce their spending by 10.39% as a result of a 1% increase in the number of dishonest judgment debtors nearby. Utilizing our rich demographic data, we investigate cross-sectional heterogeneity and demonstrate that unmarried people, men, people with education levels below the high school level, younger people, and rent payers are more likely to reduce spending than other consumers. In addition, we find that people become more cautious about their consumption of non-necessities when the percentage of dishonest judgment debtors in the area increases than when this percentage is smaller. By exploring the mechanism through which the number of dishonest judgment debtors affects consumption, we verify a positive relationship between information searches and the actual number of dishonest judgment debtors, indicating that local people are aware of this information and adjust their spending behavior accordingly. We present a collection of evidence supporting our causal interpretation and mechanism by exploiting the risk associated with personal backgrounds and clarifying the predictive ability of the number of dishonest judgment debtors. Our findings suggest that the adjustment of consumption behavior in response to the number of local dishonest judgment debtor is not necessarily driven by specific information on dishonest judgment debtors. Rather than altering credit supply, the disclosure of the number of dishonest judgment debtor can lead to a change in consumer credit demand behavior. Specifically, we examine how individual consumption reacts to exogenous variations in the number of local dishonest judgment debtors in a DID setting to eliminate endogeneity concerns. Overall, this study provides new evidence for the role of regional factors in shaping consumption decisions and highlights the need to include regional power when assessing the aggregate impact of these factors.

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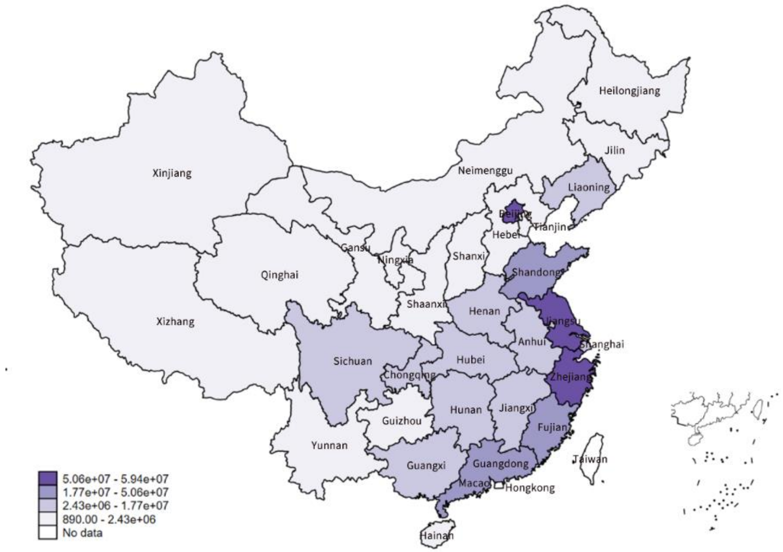
Figure 1. Distribution of Dishonest Judgment Debtors

Panel A: Distribution of Dishonest Judgment Debtors **by Location**

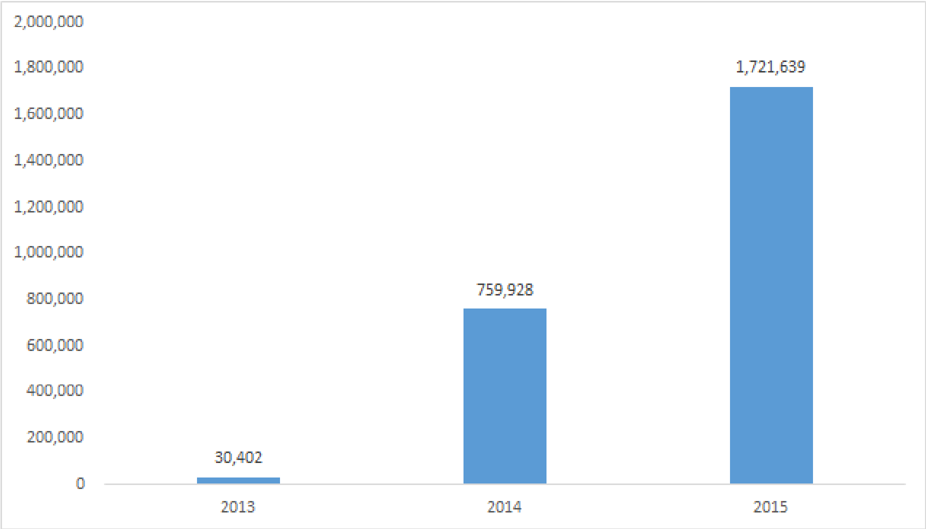
(1) Monthly Average Dishonest Judgment Debtors

(2) Total Dishonest Judgment Debtors **during the Sample Period**

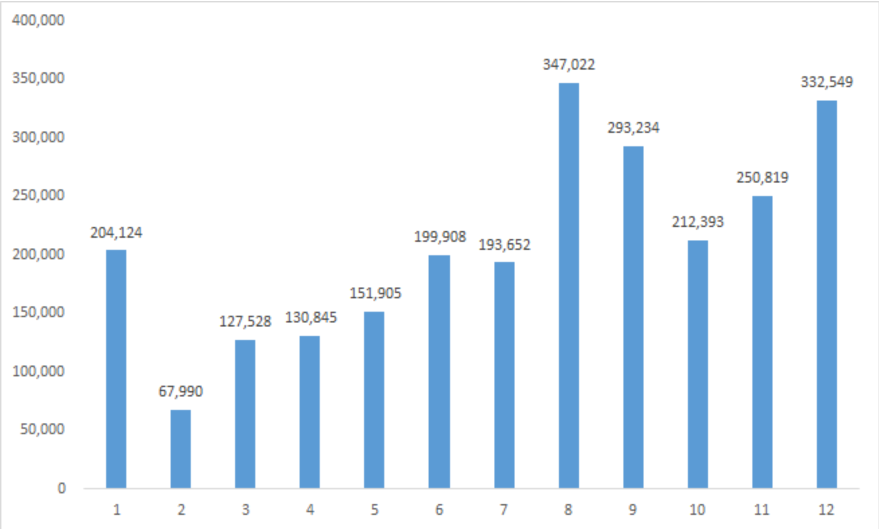


Panel B: Distribution of Dishonest Judgment Debtors over Time

(3) Distribution by year

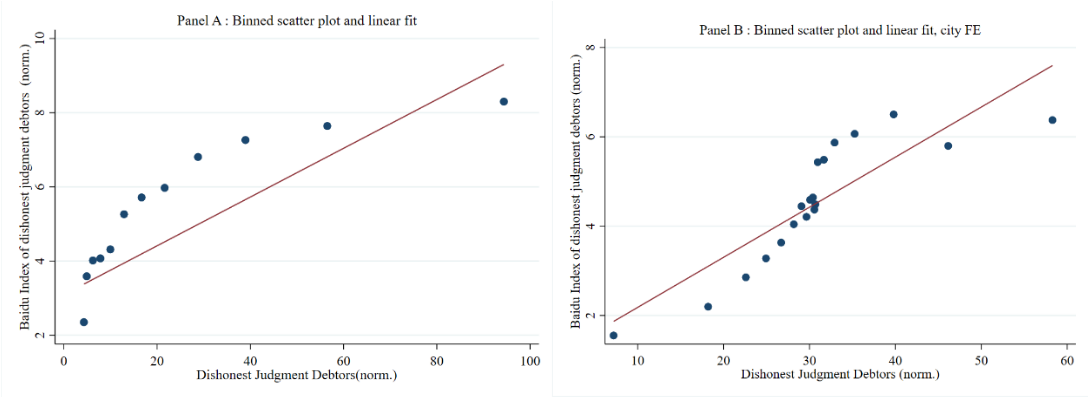


(4) Monthly distribution



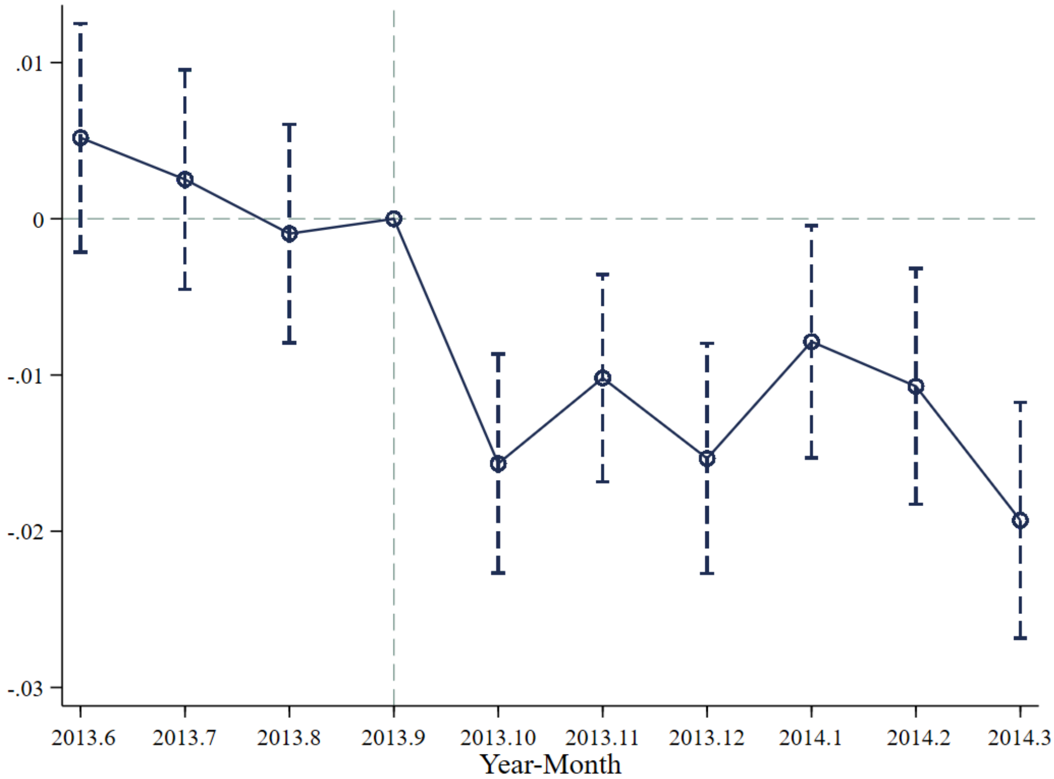
Notes: This figure plots the geographical distribution and time distribution of raw number of dishonest judgment debtors (without scaling by local population), who fail to fulfill court orders in the court's jurisdiction in our sample from October 2013 to December 2015.

Figure 2. Attention Given to Dishonest Judgment Debtors: Baidu Searches and Actual Dishonest Judgment Debtors



Notes: This figure examines the correlation between Baidu searches for the word "Dishonest judgment debtors" and the raw number of defaulters at the city-month level. Panel A shows a binned scatter plot including a linear fit pooling data. Panel B shows the same plot after partialing out city fixed effects. The number of monthly dishonest judgment debtors and the number of monthly Baidu searches index are each normalized to be within the interval [0, 100] for each city over the sample period. The sample period is from October 2013 to December 2015.

Figure 3. The Dynamic Impact of Dishonest Judgment Debtors on Consumption



Notes: The figure visualizes the dynamic effect of dishonest judgment debtors on consumption between June 2013 and March 2014, using September 2013 as the reference, where the solid line connects the estimates and the dashed line indicates the 95% confidence intervals.

Table 1: Summary Statistics

VARIABLE	N	Mean	Std.	Min	Max
	Panel A: Consumer-level variables				
Average monthly consumption	9,179,847	3619.057	10511.09	0	494,321
Number of purchases	9,179,847	2.0214	4.2221	0	994
Age	432,088	37.9291	9.0784	18	92
Male (%)	432,088	0.5577	0.4967	0	1
Married (%)	432,088	0.7268	0.4456	0	1
Own (%)	432,088	0.8920	0.3104	0	1
High-school and below (%)	432,088	0.1713	0.3768	0	1
	Panel B: Court-level variables				
Monthly Raw Number of DJD	58,431	38.2351	209.8086	0	10,838
Monthly Scaled Number of DJD	58,431	0.00007	0.0004	0	0.016
	Panel C: Credit card application and approval data				
Monthly Raw Number of applications	54,054	264.7367	339.5454	1	11,211
Monthly Raw Number of approved applications	54,054	71.9700	113.1038	0	3,334
	Panel D: Additional variables				
Ln disposable income of urban household per capita	837	3.6655	0.1055	3.4082	4.1099
Consumer price index	837	101.7881	0.7416	99.9	104.3
Ln local GDP per capita	248	4.0259	0.1435	3.7128	4.4860
Local unemployment rate	62	3.4140	0.5078	1.2	4.5
Country stock return	27	0.0475	0.1034	-0.1664	0.2701

Notes**:* This table reports the summary statistics of our credit card sample. In the analysis sample, we exclude individuals younger than 18 years of age. ***Age is the individual card holder's age in the transaction year. ***Male*** is a dummy variable that equals 1 if the credit card holder is a man, and 0 otherwise. ***Married*** is a dummy variable that equals 1 if the credit card holder is married, and 0 otherwise. ***Own*** is a dummy variable that equals 1 for homeowners, and 0 otherwise. ***High school and below*** is a dummy variable that equals 1 if the credit card holder has high school education experience or above, and 0 otherwise. ***DJD (dishonest judgment debtors)*** is the number of people per month who fail to fulfill court orders in the court's jurisdiction divided by the number of people in the court's jurisdiction in the previous calendar year, expressed in percentage terms. ***Monthly Raw Number of Applications*** is the number of people who apply for new credit cards in this court per month. ***Monthly Raw Number of Approved Applications*** is the number of people per month who apply for new credit cards and receive bank approval in this court. ***Local unemployment rate*** is a yearly province-level unemployment rate (in percentage terms) from the China National Bureau of Statistics. ***Ln local GDP per capita*** is the natural logarithm of quarterly province-level GDP per capita. ***Country stock return*** is the monthly market value-weighted stock return of China A-shares from CSMAR. ***Ln disposable***

income of urban household per capita is the natural logarithm of the disposable income per capita per month of urban residents in the province, which is collected from the China National Bureau of Statistics. ***Consumer price index*** (based on the same month last year) is expressed at the province-month level.

Table 2: Consumption Response to Local Dishonest Judgment Debtors

VARIABLE	(1) $Log(C_t)$	(2) $Log(C_t)$	(3) $Log(C_t)$	(4) $Log(C_t)$	(5) $Log(C_t)$	(6) $Log(C_t)$	(7) $Log(C_t)$
DJD_t	-9.619***				-8.342**	-7.804**	-7.089**
	(-2.85)				(-2.64)	(-2.53)	(-2.26)
DJD_{t-1}		-10.388***			-9.211**	-8.243**	-7.362**
		(-2.86)			(-2.69)	(-2.60)	(-2.38)
DJD_{t-2}			-8.333**			-7.145**	-6.093**
			(-2.63)			(-2.59)	(-2.51)
DJD_{t-3}				-4.980			-4.141
				(-1.59)			(-1.53)
Constant	16.913***	-16.382***	-16.410***	-17.626***	-16.326***	-16.291***	-17.476***
	(-3.78)	(-3.60)	(-3.45)	(-3.63)	(-3.59)	(-3.45)	(-3.65)
Observations	9,179,847	8,840,711	8,501,575	8,162,439	8,835,408	8,488,990	8,146,530
R-squared	0.438	0.444	0.449	0.455	0.444	0.449	0.455
Controls				YES			
Individual FE				YES			
City FE				YES			
Year-Month FE				YES			
Cluster				Individual Year-month			

***Notes**:* This table examines the effect of local dishonest judgment debtors on consumption. DJD_t is the Dnumber of people per month who fail to fulfill court orders in the court's jurisdiction divided by the number of people in the court's jurisdiction in the previous calendar year, expressed in percentage terms. $Log(C_t)$ is the logarithm of consumers' monthly spending at time *t*. All specifications control for last quarter's seasonally adjusted log of GDP per capita and last year's unemployment rate at the provincial level, the seasonally adjusted log of the disposable income of urban households per capita, and the consumer price index (based on the same month last year) at the province-month level. Standard errors are two-way clustered at the individual and year-month level. The t-statistics are reported in parentheses under the coefficients, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Spatial Proximity: City Level

VARIABLE	(1) $Log(C_t)$	(2) $Log(C_t)$	(3) $Log(C_t)$	(4) $Log(C_t)$
DJD_t	-0.011***			
	(-3.76)			
DJD_{t-1}		-0.010***		
		(-3.39)		
DJD_{t-2}			-0.009***	
			(-3.26)	
DJD_{t-3}				-0.006
				(-1.63)
Constant	-15.943***	-15.967***	-15.552***	-17.084***
	(-3.65)	(-3.51)	(-3.33)	(-3.61)
Observations	9,179,847	8,840,711	8,501,575	8,162,439
R-squared	0.438	0.444	0.449	0.455
Controls	YES			
Individual FE	YES			
City FE	YES			
Year-Month FE	YES			
Cluster	Individual Year-month			

Notes: This table examines the effect of city-level dishonest judgment debtors on consumption. DJD_t is the number of people per month who fail to fulfill court orders in the court's jurisdiction divided by the number of people in the court's jurisdiction in the previous calendar year, expressed in percentage terms. $Log(C_t)$ is the logarithm of consumers' monthly spending at time *t*. All specifications control for last quarter's seasonally adjusted log of GDP per capita and last year's unemployment rate at the provincial level, the seasonally adjusted log of the disposable income of urban households per capita, and the consumer price index (based on the same month last year) at the province-month level. Standard errors are two-way clustered at the individual and year-month level. The t-statistics are reported in parentheses under the coefficients, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Cross-Sectional Heterogeneity: By Consumer Characteristics

VARIABLE	(1) $Log(C_t)$	(2) $Log(C_t)$	(3) $Log(C_t)$	(4) $Log(C_t)$	(5) $Log(C_t)$
DJD_{t-1}	-37.418***	-5.338	-7.258**	0.427	-37.143**
	(-2.91)	(-1.40)	(-2.12)	(0.08)	(-2.19)
DJD_{t-1} ×Married	37.487**				
	(2.46)				
DJD_{t-1} ×Male		-8.943*			
		(-1.78)			
DJD_{t-1} ×Highschool			-14.261*		
			(-1.88)		
DJD_{t-1} ×Age35				-26.222**	
				(-2.26)	
DJD_{t-1} ×Owner					29.640*
					(1.78)
Constant	16.390***	-16.385***	-16.383***	-16.382***	-16.383***
	(-3.60)	(-3.60)	(-3.60)	(-3.60)	(-3.60)
Observations	8,840,711	8,840,711	8,840,711	8,840,711	8,840,711
R-squared	0.444	0.444	0.444	0.444	0.444
Controls			YES		
Individual FE			YES		
Court FE			YES		
Year-month FE			YES		
Cluster			Individual Year-month		

Notes: This table shows the heterogeneity of responses by consumer characteristics. Please refer to Table 1 for detailed variable definitions. DJD_t is the number of people per month who fail to fulfill court orders in the court's jurisdiction divided by the number of people in the court's jurisdiction in the previous calendar year, expressed in percentage terms. $Log(C_t)$ is the logarithm of consumers' monthly spending in time *t*. All specifications control for last quarter's seasonally adjusted log of GDP per capita and last year's unemployment rate at the provincial level, the seasonally adjusted log of the disposable income of urban households per capita, and the consumer price index (based on the same month last year) at the province-month level. Standard errors are two-way clustered at the individual and year-month level. The t-statistics are reported in parentheses under the coefficients, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Consumption Response by Type of Spending

VARIABLE	(1) Necessities $Log(C_t)$	(2) Non-necessities $Log(C_t)$
DJD_{t-1}	0.643	-7.620***
	(0.23)	(-3.06)
Constant	1.619	-2.614
	(0.32)	(-1.02)
Observations	8,840,711	8,840,711
R-squared	0.430	0.280
Controls	YES	
Individual FE	YES	
Court FE	YES	
Year-Month FE	YES	
Cluster	Individual Year-month	

***Notes**:* This table shows the consumption response by spending type. The dependent variables for columns (1) and (2) are the logarithm of monthly consumption on necessities and non-necessities, respectively. Please refer to Table 1 for detailed variable definitions. DJD_t is the number of people per month who fail to fulfill court orders in the court's jurisdiction divided by the number of people in the court's jurisdiction in the previous calendar year, expressed in percentage terms. All specifications control for last quarter's seasonally adjusted log of GDP per capita and last year's unemployment rate at the provincial level, the seasonally adjusted log of the disposable income of urban households per capita, and the consumer price index (based on the same month last year) at the province-month level. Standard errors are two-way clustered at the individual and year-month level. The t-statistics are reported in parentheses under the coefficients, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Are Dishonest Judgment Debtors Predictive?

VARIABLE	(1) ln GDP $per\ capita$	(2) $Local$ $unemplyment$	(3) $Stock$ $market\ return$
DJD_{t-1}	0.002	0.003	0.000
	(0.55)	(0.13)	(0.78)
DJD_{t-2}	0.000	-0.009	-0.000
	(0.11)	(-0.36)	(-0.58)
DJD_{t-3}	-0.002	0.017	-0.000
	(-0.84)	(1.32)	(-0.31)
DJD_{t-4}	0.000	-0.010	-0.000
	(0.15)	(-1.02)	(-0.65)
DJD_{t-5}	-0.001	0.007	0.000
	(-0.35)	(0.56)	(0.53)
DJD_{t-6}	-0.002	0.004	-0.000
	(-0.67)	(0.74)	(-0.68)
Constant	9.599***	2.981***	0.059
	(286.97)	(4.30)	(1.64)
Spatial unit	Province	Province	Country
Time unit	Quarter	Year	Month
Spatial FE	YES	YES	NO
Time FE	YES	YES	NO

Notes: This table examines whether local dishonest judgment debtors are predictive of economic conditions or future returns. DJD_{t-k} is the k-th (monthly, quarterly, or yearly) lag of the number of dishonest judgment debtors in the geographical unit and time unit, scaled by the number of people in that geographical unit in the previous calendar year. ln $GDP\ per\ capita$ is measured at the province-quarter level. $Local\ unemployment$ is measured at the province-year level. $Stock\ market\ return$ is the monthly market value-weighted return of A-shares on the Chinese stock market. Standard errors are clustered at the court level. The t-statistics are reported in parentheses under the coefficients, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Do Dishonest Judgment Debtors Affect Credit Demand and supply?

VARIABLE	(1)	(2) Applicants$_t$	(3)	(4)	(5) Approval$_t$	(6)
DJD_t	-0.004***			0.006		
	(-2.89)			(1.14)		
DJD_{t-1}		-0.006***			0.005	
		(-4.47)			(0.72)	
DJD_{t-2}			-0.003*			0.002
			(-1.72)			(0.38)
Constant	179.123***	181.180***	182.678***	72.175***	73.124***	73.811***
	(4,925.81)	(5,145.55)	(5,029.34)	(548.69)	(442.56)	(503.87)
Observations	54,054	51,597	49,140	54,054	51,597	49,140
R-squared	0.807	0.807	0.807	0.499	0.499	0.497
Court FE	YES					
Year-month FE	YES					
Cluster	Court					

***Notes**:* This table examines the effect of local dishonest judgment debtors on the number of new credit card applications in column (1)- (3) and the number of approved new credit card applications in column (4)- (6). DJD_t is the number of people per month who fail to fulfill court orders in the court's jurisdiction divided by the number of people in the court's jurisdiction in the previous calendar year, expressed in percentage terms. The dependent variable $Applicants$ in column (1)- (3) is the number of credit card applicants within a court in a month. The dependent variable $Approval$ in column(4)-(6) is the number of approved credit card applicants within a court in a month. Standard errors are clustered at the court level. The t-statistics are reported in parentheses under the coefficients, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Background Risks

	(1) Excluding Consumers Working in Cyclical Industries	(2) Excluding Consumers Working in the Non-Tradable Sector
VARIABLE	$Log(C_t)$	$Log(C_t)$
DJD_{t-1}	-10.094***	-9.790***
	(-2.96)	(-2.81)
Constant	-13.496***	-12.552**
	(-2.98)	(-2.64)
Observations	7,387,771	6,609,225
R-squared	0.450	0.452
Controls	YES	
Individual FE	YES	
Court FE	YES	
Year-Month FE	YES	
Cluster	Individual Year-month	

Notes: This table shows the robustness checks to address the possibility that our findings reflect unobserved changes in background risks. In column 1, we re-estimate our main specification excluding individuals working in cyclical industries. In column 2, we re-estimate our main specification excluding individual working in non-tradable industries. DJD_t is the number of people per month who fail to fulfill court orders in the court's jurisdiction divided by the number of people in the court's jurisdiction in the previous calendar year, expressed in percentage terms. All specifications control for last quarter's seasonally adjusted log of GDP per capita and last year's unemployment rate at the provincial level, the seasonally adjusted log of the disposable income of urban households per capita, and the consumer price index (based on the same month last year) at the province-month level. Standard errors are two-way clustered at the individual and year-month level. The t-statistics are reported in parentheses under the coefficients, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

DTable 9: Alternative Consumption Measures: Number of Purchases

VARIABLE	(1) $Log(\mathrm{P}_t)$	(2) $Log(\mathrm{P}_t)$	(3) $Log(\mathrm{P}_t)$	(4) $Log(\mathrm{P}_t)$
DJD_t	-4.630			
	(-1.52)			
DJD_{t-1}		-8.165***		
		(-3.11)		
DJD_{t-2}			-6.765**	
			(-2.56)	
DJD_{t-3}				-1.714
				(-0.56)
Constant	-12.567***	-12.769***	-13.179***	-13.941***
	(-3.23)	(-3.19)	(-3.17)	(-3.22)
Observations	9,179,847	8,840,711	8,501,575	8,162,439
R-squared	0.499	0.505	0.511	0.517
Controls	YES			
Individual FE	YES			
Court FE	YES			
Year-Month FE	YES			
Cluster	Individual Year-month			

***Notes**:* This table examines the effect of local dishonest judgment debtors on the number of purchases. DJD_t is the number of people per month who fail to fulfill court orders in the court's jurisdiction divided by the number of people in the court's jurisdiction in the previous calendar year, expressed in percentage terms. $Log(\mathrm{P}_t)$ is consumers' monthly number of purchases at time *t*. All specifications control for last quarter's seasonally adjusted log of GDP per capita and last year's unemployment rate at the provincial level, the seasonally adjusted log of the disposable income of urban households per capita, and the consumer price index (based on the same month last year) at the province-month level. Standard errors are two-way clustered at the individual and year-month level. The t-statistics are reported in parentheses under the coefficients, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Alternative Dishonest Judgment Debtors Measures

VARIABLE	(1) $Log(\mathrm{C}_t)$	(2) $Log(\mathrm{C}_t)$
$Log\ raw\ DJD_{t-1}$	-0.007***	
	(-3.24)	
Quartile DJD_{t-1}		-0.006***
		(-2.53)
Constant	-16.075***	-16.450***
	(-3.52)	(-3.60)
Observations	8,840,711	8,840,711
R-squared	0.444	0.444
Controls	YES	
Individual FE	YES	
Court FE	YES	
Year-Month FE	YES	
Cluster	Individual Year-month	

***Notes**:* This table displays the different transformations of the raw number of dishonest judgment debtors, the monthly number of people who fail to fulfill court orders in the court's jurisdiction, specifically taking the logarithm of the raw number of dishonest judgment debtors($Log\ raw\ DJD_t$),and a variable(Quartile DJD_{t-1}) reaching from one to four indicating in which quartile among observations from that court's jurisdiction over the sample period the dishonest judgment debtors measure lies. All specifications control for last quarter's seasonally adjusted log of GDP per capita and last year's unemployment rate at the provincial level, the seasonally adjusted log of the disposable income of urban households per capita, and the consumer price index (based on the same month last year) at the province-month level. Standard errors are two-way clustered at the individual and year-month level. The t-statistics are reported in parentheses under the coefficients, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Placebo Analysis

	(1) DJD Assigned from Same Period but Randomly Drawn Court	(2) DJD Assigned from Same Court but Randomly Drawn Period
VARIABLE	$Log(C_t)$	$Log(C_t)$
DJD_{t-1}	0.216	1.203
	(0.06)	(0.31)
Constant	3.503***	3.544***
	(3.26)	(2.88)
Observations	8,840,711	8,840,711
R-squared	0.438	0.427
Controls	YES	
Individual FE	YES	
Court FE	YES	
Year-Month FE	YES	
Cluster	Individual Year-month	

***Notes**:* This table presents the results of placebo tests in which we re-estimate equation 2. In column 1 , for each court-month observation, DJD_t, the scaled number of dishonest judgment debtors (the number of people per month who fail to fulfill court orders in the courDt's jurisdiction divided by the number of people in the court's jurisdiction in the previous calendar year, expressed in percentage terms) is randomly drawn from the set of all court-level dishonest judgment debtors occurring in the relevant month. In column 2, for each court, DJD_t is randomly drawn from the set of all monthly dishonest judgment debtors realizations that occur within the relevant court over the sample period. Dishonest judgment debtors is the number of people per month who fail to fulfill court orders in the court's jurisdiction divided by the number of people in the court's jurisdiction in the previous calendar year, expressed in percentage terms. All specifications control for last quarter's seasonally adjusted log of GDP per capita and last year's unemployment rate at the provincial level, the seasonally adjusted log of the disposable income of urban households per capita, and the consumer price index (based on the same month last year) at the province-month level. Standard errors are two-way clustered at the individual and year-month level. The t-statistics are reported in parentheses under the coefficients, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Influence of inactive account and outliers

	(1) Consumers active more than 6 months	(2) Consumers active more than 9 months	(3) Consumers active more than 12 months	(4) Influence of Outlier Courts	(5) Influence of Outlier Consumers
VARIABLE	$Log(\mathrm{C}_t)$	$Log(\mathrm{C}_t)$	$Log(\mathrm{C}_t)$	$Log(\mathrm{C}_t)$	$Log(\mathrm{C}_t)$
DJD_{t-1}	-11.214**	-10.527**	-11.556**	-10.105**	-10.190***
	(-2.75)	(-2.39)	(-2.39)	(-2.78)	(-2.89)
Constant	-17.037***	-15.291**	-12.931**	-16.797***	-15.119***
	(-3.13)	(-2.73)	(-2.29)	(-3.56)	(-3.31)
Observations	6,643,791	5,770,310	4,909,456	8,643,934	8,141,755
R-squared	0.318	0.278	0.248	0.443	0.426
Controls			YES		
Individual FE			YES		
Court FE			YES		
Year-Month FE			YES		
Cluster			Individual Year-month		

***Notes**:* This table reports the effect of inactive account and outliers. In column 1, we exclude all consumers whose average monthly consumption for more than 6 months is 0 during the sample time and estimate the consumption response for the remaining consumers. In column 2, we exclude all consumers whose average monthly consumption for more than 9 months during the sample time is 0 and estimate the consumption response for the remaining consumers. In column 3, we exclude all consumers whose average monthly consumption for more than 12 months during the sample time is 0 and estimate the consumption response for the remaining consumers. In column 4, we exclude all courts with DJD_t (the number of people per month who fail to fulfill court orders in the court's jurisdiction divided by the number of people in the court's jurisdiction in the previous calendar year, expressed in percentage terms) above the 99th percentile in the sample period, and estimate the consumption response for the remaining courts. In column 5, we exclude all consumers with consumption above the 99th percentile, and estimate the consumption response for the remaining observations.

Table 13: The Impact of Dishonest Judgment Debtors

VARIABLE	(1) $Log(C_t)$	(2) $Log(C_t)$
$ln\,DJD_{2013.10}$ × post	-0.017***	-0.014***
	(-8.18)	(-5.91)
$lnPopulation$ × post		-0.016***
		(-3.11)
Constant	3.649***	3.595***
	(1,223.80)	(203.94)
Observations	4,320,880	4,320,880
R-squared	0.497	0.497
Individual FE	YES	
Year-month FE	YES	
Court FE	YES	
Cluster	Individual	

Notes: This table reports the impact of dishonest judgment debtors on consumption before and after October 2013. It displays the estimates of the model in equation 1. $ln\,DJD_{2013.10}$ is the log of the monthly number of people who fail to fulfill court orders in the court's jurisdiction in October 2013 divided by the number of people in the court's jurisdiction in the previous calendar year, expressed in percentage terms. Post is 0 for all months before October 2013 and 1 after October 2013. $lnPopulation$ is the log of the yearly population in the court's jurisdiction. Standard errors are clustered at the individual level. The t-statistics are reported in parentheses under the coefficients, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Table A1: Variations in the number of dishonest judgment debtors

	DJD_t						
VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DJD_{t-1}				0.307***	0.159***	0.147***	0.126***
				(11.58)	(6.56)	(5.89)	(5.02)
DJD_{t-2}						-0.007	-0.025**
						(-0.59)	(-2.04)
DJD_{t-3}						0.003	-0.012
						(0.21)	(-0.94)
DJD_{t-4}							-0.019
							(-1.54)
DJD_{t-5}							-0.019
							(-1.39)
DJD_{t-6}							-0.043**
							(-2.46)
Observations	65,988	65,988	65,988	63,544	63,544	58,656	51,324
R-squared	0.018	0.160	0.178	0.091	0.202	0.210	0.224
Court FE	NO	YES	YES	NO	YES	YES	YES
Month FE	YES	NO	YES	NO	YES	YES	YES
Cluster	Court	Court	Court	Court	Court	Court	Court

***Notes*:** This table examines the sources of variation and autocorrelation of the measure of dishonest judgment debtors (DJD_t). It displays the OLS regression of the measure of dishonest judgment debtors on monthly time effects (column 1), court fixed effects (column 2), both (column 3), its own lag (column 4), month fixed effects, court fixed effects, and its first lag (column 5). Columns 6 and 7 add additional lags to the specification in column 5. DJD_t is the number of people per month who fail to fulfill court orders in the court's jurisdiction divided by the number of people in the court's jurisdiction in the previous calendar year, expressed in percentage terms. $DJD_{t-\mathrm{k}}$ indicates the *k*-th monthly lag of the number of dishonest judgment debtors. The sample period is from October 2013 to December 2015. The t-statistics are reported in parentheses under the coefficients, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.