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Public Credit Information Arrangements and Entrepreneurship: Evidence from China

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Abstract: This paper examines how improved public credit information arrangements affect entrepreneurial activities and interact with traditional informal institutions. From 2015 to 2016, the Chinese government implemented a Credit Demonstration City Construction (CDCC) program, which utilized big data technologies to promote credit information sharing and facilitate the usage of public credit information. Using a difference-in-differences approach, we find that the CDCC program improved credit information disclosure and promoted

entrepreneurial activities. We provide some evidence for the mechanism that the improved public credit information arrangements alleviated entrepreneurs' credit constraints and lowered the risks of running businesses. In addition, we find that the effects of the CDCC program are stronger in areas where Confucian culture and Buddhism are less prevalent, suggesting that formal and informal institutions may serve complementary functions in promoting entrepreneurship.

Keywords: business risks; credit constraints; credit information arrangements; entrepreneurship; informal institution

1 Introduction

Entrepreneurship is widely considered as the engine of economic growth and a catalytic agent for the expansion and promotion of productive activities. However, potential entrepreneurs usually face the problems of credit constraints and risky business environments, especially in developing countries with underdeveloped credit institutions (McMillan & Woodruff 2002; Acs & Virgill 2010). Traditional informal institutions, such as religions, social norms, and kinship may alleviate these problems by providing informal channels for credit information sharing and external financing (North 1991, 2012; Cacciotti & Hayton 2017). To provide formal services of sharing credit information and safeguarding creditor rights, an increasing number of countries have established private credit bureaus and public credit registration systems. Although an increasing number of studies have examined the effects of credit information arrangements on credit market performance (De Janvry *et al.* 2010; Sutherland 2018; Choudhary & Jain 2020; Liberti *et al.* 2022), few studies have examined their impacts on entrepreneurial activities and their interaction with traditional informal institutions.

This paper aims to address two questions: (1) Do public credit information arrangements promote entrepreneurial activities? (2) How do the effects of public credit information arrangements on entrepreneurial activities vary with the prevalence of informal institutions? We focus on China's credit institution reform. Traditionally, the allocation of trade credit is highly dependent on social networks of acquaintances, and informal institutions such as clans, Buddhism, and Confucianism are important for maintaining business relationships (Greif & Tabellini 2010; Zhang 2020; Chen *et al.* 2022). During 2015–2016, the National Development and Reform Commission (NDRC) and the People's Bank of China (PBC) approved a total of 41 out of 333 cities to implement the Credit Demonstration City Construction (CDCC) program. The primary objective of the program is to enhance the disclosure of public credit information through big data technologies and facilitate its usage in economic activities.

Exploiting the staggered implementation of the CDCC program, we employ a difference-in-differences (DID) strategy. Using data crawled from national credit websites, we verify that the CDCC program significantly improved credit information disclosure. Employing data from the 2011–2019 waves of the China Household Finance Survey (CHFS), we show that the CDCC program promoted entrepreneurship and entrepreneurial investment. We demonstrate minimal bias caused by several endogeneity issues, including the violation of parallel trends assumptions, the omitted variable problem associated with concurrent policy shocks, the sample selection issue, and the negative weight problem of the staggered DID model.

We then provide some suggestive evidence for the channels through which the CDCC program worked. First, the CDCC program significantly decreased the interest rate on entrepreneurial loans and increased the probability of obtaining enterprise loans, which suggests alleviated credit constraints on entrepreneurs. Second, the CDCC program increased the probability of having accounts receivable held by entrepreneurs, which suggests lowered default risks in business activities. Third, the CDCC program promoted enterprises to develop formal organizations, expand production, and survive in the market. We argue that formal, large, and old enterprises might gain more sources of funding and experience lower default risks due to the provision of public credit information.

Furthermore, we explore the interactions between formal credit institutions and traditional informal institutions. We show that the effects of the CDCC program are stronger in areas where Confucian culture and Buddhism are less prevalent. Similar to public credit institutions, Confucian culture and Buddhism play an important role in sharing credit information among strangers and providing external sources of finance. Therefore, these informal institutions and credit institutions may serve complementary functions in promoting entrepreneurship. However, we find little evidence that the effects of the CDCC program vary across cities with the prevalence of clan culture. A potential explanation is that clan-based organizations primarily serve acquaintances within the same clan rather than the general population.

Our paper contributes to three lines of literature. First, we contribute to the literature on the socioeconomic effects of credit information sharing arrangements. Previous cross-country comparison studies have typically revealed positive associations between the presence of credit information-sharing arrangements and credit market outcomes (Jappelli & Pagano 2002; Djankov *et al.* 2007). To avoid country-level confounding factors, a growing body of recent literature has leveraged experimental or quasi-experimental designs to identify the causal effects of credit information arrangements (De Janvry *et al.* 2010; Doblas-Madrid & Minetti 2013; De Haas *et al.* 2021; Liberti *et al.* 2022). For example, Behr and Sonnekalb (2012)

evaluated the effect of a public credit registry reform in Albania and found that improved information sharing among lenders decreased the frequency of default behavior among borrowers. Sutherland (2018) exploited the staggered entry of lenders into a credit information sharing bureau and showed that credit information sharing decreased relationship lending. Choudhary and Jain (2020) evaluated the effect of a Pakistani banking reform that decreased public credit information available to lenders. They found that reduced public credit information exacerbated the issue of adverse selection in the lending market. This study provides novel evidence that public credit information arrangements can further promote entrepreneurial activities in a transition economy.

Second, our study is related to the literature on entrepreneurship in developing countries. Potential entrepreneurs in developing countries typically encounter severe financial constraints, and they usually rely on internal finance or raise funds through informal institutions (Acs & Virgill 2010; Kerr & Nanda 2011). Previous studies have documented that financial policies extending loans from the formal banking sector to financially constrained individuals can help small businesses to develop (Field *et al.* 2013; Angelucci *et al.* 2015; Augsburg *et al.* 2015; Banerjee *et al.* 2015; Crépon *et al.* 2015; Meager 2019). However, the difficulty to assess the default risks prohibits such policies from being widely adopted in developing countries (Cull & Morduch 2018). We show that public credit information arrangements can both alleviate financial constraints and reduce default risks, thereby promoting entrepreneurial activities. This may provide important development policy insights for other developing countries with underdeveloped credit information markets.

Third, our study speaks to the literature examining the interaction between formal and informal institutions. A growing body of recent literature has examined the interactions between formal and informal institutions (Casson *et al.* 2010; Bisin & Verdier 2017; Bau 2021). For example, Guiso and Pinotti (2013) found that voting rights extension on regional voting participation rates in Italy depended on the level of civic capital. Martinez-Bravo *et al.* (2017) showed that clan culture moderated the performance of formal democratic institutions in public good provision in rural China. We provide new evidence that informal institutions may also moderate the effects of formal credit institutions on entrepreneurship when these institutions serve the same population.

The rest of the paper is organized as follows. Section 2 provides an overview of entrepreneurship and credit information arrangements in China and outlines a brief conceptual framework for the empirical analysis. Section 3 describes the data and the empirical strategy employed in the empirical analysis. Section 4 presents the estimation results for entrepreneurial

activities, investigates the underlying mechanisms, and discusses the interactions between formal and informal institutions. Section 5 concludes.

2 Background and conceptual framework

2.1 Entrepreneurship in China

Private enterprises in China have grown rapidly over the last twenty years. According to the National Bureau of Statistics (NBS) of China, the number of persons working in private enterprises and state-owned enterprises in urban areas was 34 and 81 million in 2000. By 2018, the number of employed persons in state-owned enterprises in urban areas had decreased by 29% but the number of persons working in private enterprises had increased more than six times. Assets of enterprises in the same period showed a similar differential trend, with assets of state-owned companies showing a 38% increase but assets of private enterprises increasing about 60 times.

Despite the rapid growth of the private sector, private entrepreneurs still face severe credit constraints (Poncet *et al.* 2010; Guariglia *et al.* 2011). According to the 2013 wave of the CHFS, about 51.4% of entrepreneurs could not obtain loans from banks when encountering financing problems in the early stage of their business, and the two most prominent reasons for low credit accessibility were the lack of collateral and the absence of third party guarantees. The problems of credit constraints might lead to reductions in entrepreneurial participation, firm size, and aggregate capital (Ma *et al.* 2019).

Moreover, the problems of contract enforcement are severe in China. According to the data released by the National Development and Reform Commission, courts across the country reported a total of 14.42 million serious defaulters between 2013 and 2019, accounting for about 1% of the country's total population. According to the data released by the State Administration for Market Regulation, a total of 6,648,600 enterprises had been reported abnormal business operations, and 982,400 enterprises had been reported serious illegal and dishonest behavior by the end of 2020. Such weak contract enforcement might result in a risky business environment, which was harmful to entrepreneurial activities (Acs & Virgill 2010).

2.2 Public credit system in China

Traditionally, credit information sharing in China relies heavily on social and economic relationships among extended family members and acquaintances. These relationships also play an important role in raising external funds, enforcing private contracts, and imposing effective sanctions on defaulters (Greif & Tabellini 2010; Zhang 2020; Chen *et al.* 2022). Entrepreneurs,

especially new ones, often receive support from traditional social networks such as family, friends, and community members. In comparison, modern developed countries usually establish formal credit agencies or bureaus to evaluate the creditworthiness of individuals and firms. A desirable feature of formal credit institutions is that they can expand the scale of economic activities beyond personal relationships and collect credit information more efficiently (De Haas *et al.* 2021).

For a long time, China lacked a formal national credit system. After the market-oriented reform in 1978, the poor enforcement of contracts between economic agents made the construction of formal credit institutions increasingly important. Some large banks established their own credit systems to evaluate the creditworthiness of individuals and firms but did not share credit information with the public. Consequently, credit unworthy individuals or firms could still escape punishment by moving to another city. In 2002, the 16th National Congress of the Party proposed the concept of the public credit system. In 2014, the State Council of China issued the "Planning Outline for the Construction of a Social Credit System (2014-2020)", which opened the curtain of improving public credit information arrangements in China. The NDRC and the PBC then jointly issued a document that appointed a selection of pilot cities to experiment with the CDCC program. During 2015–2016, a total of 41 pilot cities were selected to experiment with the program. The first batch of 11 cities was selected in 2015. The second batch of 30 cities was selected in 2016. These pilot cities are shown in Table A1 of the Appendix.

A primary objective of the CDCC program is to promote the disclosure of credit information based on big data technologies. Each pilot city established authoritative platforms to collect credit information of economic agents and share it on a national platform. To consolidate data from various records, the program mandated the establishment of a unified credit coding system for businesses. Economic agents can query credit information of their business partners by checking the list of credit-unworthy firms and individuals from national and local credit websites. Credit China (www.creditchina.gov.cn) records individual credit information, whereas National Enterprise Credit Information Publicity System (www.gsxt.gov.cn) records credit information of firms.

Figure 1 plots the average numbers of dishonest judgment debtors and unreliable enterprises per 1,000 population in pilot and nonpilot cities over time. The data are crawled from the national credit websites (www.creditchina.gov.cn and www.gsxt.gov.cn). Before 2015, the average numbers of credit-unworthy firms and individuals in pilot cities were similar to those in nonpilot cities. After the adoption of the policy, the average numbers of dishonest judgment debtors and unreliable enterprises reported in pilot cities became significantly higher

than among those in nonpilot cities. In general, the figure suggests that pilot cities reported more information on discredited behavior due to the implementation of the CDCC program. Table A2 shows the regression analog of the graph. The estimates indicate that the implementation of the CDCC program increased the average numbers of credit-unworthy firms and individuals per 1,000 population by 0.405 (98.8% of the sample average) and 0.110 (131.0% of the sample average), respectively.

Furthermore, the CDCC program includes several additional approaches to facilitate the usage of public credit information. First, credit appraisal and supervision mechanisms were established by local authorities on the basis of credit rating information. Local authorities published red lists of trustworthy entities, blacklists of notorious defaulters and untrustworthy entities, and sometimes grey lists called "key scrutiny lists". Flagrantly dishonest individuals and entities were penalized according to the relevant laws. Moreover, credit restoration mechanisms were put in place to encourage untrustworthy entities to rectify their mistakes and improve their credit behavior. These arrangements were expected to reduce credit default risk for entrepreneurs who extended credit to established clients or business partners. Second, non-government sectors were encouraged to use credit products and services such as credit reports, credit evaluations, and credit risk warnings. Enterprises were encouraged to develop new record-based credit products available to the public. Entrepreneurs, particularly those with well-established credit histories, could leverage their credit information to secure financial support from various economic agents, including formal financial institutions, suppliers, and customers. Third, local authorities carried out campaigns to promote awareness of creditworthiness and encourage public honesty. A public credit awareness campaign, called "Honest Business Day", was held annually to publicize examples of honest and untrustworthy behavior. Free training courses on credit restoration were also provided periodically to entrepreneurs.

The NDRC and PBC also assigned independent third-party institutions (typically university departments and popular media enterprises) to evaluate the performance of pilot cities on an annual basis. The third-party institutions would provide feedback and guidance on the development of more comprehensive public credit information arrangements. There were 11 pilot cities passing the systematic evaluation in 2018 and 15 pilot cities passing the evaluation in 2019.

2.3 Conceptual framework

The essence of the CDCC program is to enhance the disclosure of public credit information through big data technologies and facilitate its usage in economic activities. The CDCC

program may have promoted entrepreneurship through the following two channels: alleviating financial constraints and reducing the risks of running businesses.

First, the CDCC program may have alleviated financial constraints. Potential entrepreneurs usually face funding problems because lenders consider it too risky to lend money to private entrepreneurs. The credit information arrangements may provide a way for people to capitalize on their credit records (Sharpe 1990; Stein 2002). With credit information revealing the creditworthiness of entrepreneurs, lenders can relax or waive collateral requirements on loans to people with good credit records (Fosu *et al.* 2020). This may raise the probability of people with good credit records obtaining the necessary capital for starting businesses as well as their chances of surviving and thriving in the market (Bennardo *et al.* 2015).

Second, the CDCC program may have lowered the risks of running businesses. On the one hand, the CDCC program may have made it easier to acquire credit information about business partners. Dishonest partners such as defaulters and frauds can be more easily recognized, avoided, and punished by the market. Knowing these consequences, rational agents will be less likely to become defaulters and frauds (Behr & Sonnekalb 2012). Consequently, the provision of public credit information can alleviate the contract enforcement problem and lower the risk of providing goods or services on credit. On the other hand, the CDCC program may have reduced the risk of competing with producers of shoddy or fraudulent goods. The improved credit information arrangements may expose producers of shoddy or fraudulent goods while exposing and appraising producers of quality products (Padilla & Pagano 2000). As dishonest producers are publicized, they will quickly be expelled from the market (Shapiro 1983; Hörner 2002).

3 Data and empirical strategy

3.1 Data sources and descriptive statistics

Our main data source comes from the CHFS. The CHFS is an ongoing, nearly nationwide, comprehensive panel survey conducted biennially by the Survey and Research Center for China Household Finance of the Southwestern University of Finance and Economics. The baseline survey was initiated in 2011 and surveyed 8,438 households from 67 cities in 25 provinces. The second wave was conducted in 2013 and surveyed 28,228 households from 165 cities in 29 provinces. The third wave was conducted in 2015 and surveyed 37,399 households from 174 cities in 29 provinces. The fourth wave was conducted in 2017 and surveyed 40,011 households from 174 cities in 29 provinces. The latest wave was conducted in 2019 and surveyed 34,643 households from 187 cities in 29 provinces. The survey gathers information on a range of topics,

including demographic characteristics, housing assets and financial wealth, debt and credit constraints, entrepreneurial activities, social welfare and insurance, and labor market outcomes. The survey respondents are typically household members who are most familiar with household economic conditions. The CHFS has been broadly used in the literature on labor market performance and entrepreneurship in China (Cai *et al.* 2018; Clark *et al.* 2019; Li *et al.* 2020). In addition, we obtain city-level socioeconomic information from various yearbooks, history books, and government websites.

Entrepreneurial activities – The CHFS gathers detailed information on entrepreneurial activities at the household level. Following previous studies, we use a general definition of entrepreneurship, which involves the identification and pursuit of new opportunities, as well as the continuous innovation and improvement of existing businesses (Acs & Virgill 2010). We employ two measures of entrepreneurship. The first measure is a dummy variable for operating household businesses, including independent businesses, transportation, leasing, online shops, and enterprises. This measure of entrepreneurship is widely adopted in the previous literature (Hurst & Lusardi 2004; Cai *et al.* 2018; Ma *et al.* 2019; Li *et al.* 2021a). The second measure is the logarithm of one plus entrepreneurial investment, which quantifies the intensity of entrepreneurial activities.

We classify limited liability companies, incorporated companies, joint ventures, and sole proprietorships as formal enterprises and classify self-employed and those without formal organization as informal enterprises. We then set two dummy variables for running formal and informal enterprises, respectively. In the mechanism analysis, we also use information on other entrepreneurial activities, including the number of employees, years of operation, and entrepreneurial revenue and profit. We split enterprises into two groups, depending on whether the number of employees is above or below three (the sample mean conditional on running businesses). Accordingly, we set two dummy variables for running small and big enterprises, respectively. Furthermore, we divide enterprises into two groups based on whether the length of operation is below or above three years and construct two dummy variables for running new and old enterprises, respectively.

Credit outcomes – The CHFS also gathers information on entrepreneurial loans and accounts receivable. Entrepreneurial loans include loans used for entrepreneurial activities and obtained from banks, other financial institutions, relatives, and friends. Accounts receivable are the amount of money owed to a firm due to its provision of goods or services based on credit. We set two dummy variables for having entrepreneurial loans and accounts receivable, respectively. Note that only the 2015–2019 waves of the CHFS contain questions on accounts

receivable.

The CHFS does not collect information on credit default risks in business activities. Instead, we use data from the China Stock Market and Accounting Research (CSMAR). The CSMAR contains information on companies listed on the Shanghai and Shenzhen stock exchanges. We focus on the sample period between 2012 and 2019 and use a dummy variable for being involved in economic judicial arbitration to measure the credit default risks of companies. Economic judicial arbitration is a less costly and faster procedure adopted by the court system to resolve economic disputes between parties. Typical economic disputes contain disputes over loans, overdue payments, arrears, guarantees, and prolonged payments between firms and banks.

We also use the CSMAR data to construct other direct and indirect measures of credit default risk. Specifically, we employ the BS index proposed by Bharath and Shumway (2008) to quantify the credit default risk of firms. This index, constructed according to the Merton DD model (Merton 1974), is widely used in previous studies (Li *et al.* 2019; Lee 2020; Chu 2021). The index is based on the idea that a firm's shareholders' equity is viewed as a call option and that a firm becomes more likely to default when its asset value falls below its debt value. The index is calculated as the difference between the firm's asset value and its debt, divided by the standard deviation of the firm's asset value. A higher value of the BS index indicates a greater distance to default, signifying a lower degree of credit default risk. We also use firms' credit loan ratio and working capital turnover to test firms' credit default risk. A high credit loan ratio indicates firms that have a higher level of credit, which suggests they may have a lower probability of credit default (Buchas *et al.* 2021). Working capital turnover directly influences the liquidity of the firm. A high working capital turnover ensures efficient and smooth functioning and higher efficiency in utilizing working capital, resulting in a reduction of credit default risk (Adhikari *et al.* 2021).

Informal institutions – Following previous studies, we use the total number of Confucian temples in a city as a proxy variable for the strength of local Confucian culture (Kung & Ma 2014; Feng *et al.* 2021; Miao *et al.* 2021a). The Confucian temples have played a vital role in the propagation and education of Confucianism in Chinese history. Consequently, the number of Confucian temples typically has a positive association with the strength of Confucian culture. Information about Confucian temple locations is manually collected from the National Choreography of the Qing Dynasty.

Following previous studies, we use the number of Buddhist temples in a city to measure the prevalence of Buddhism (Wang & Lin 2014). The reasoning behind our choice is that the

supply side of religion, or the number of religious institutions, largely determines religious culture (Stark & Finke 2000). The official website of China's State Administration for Religious Affairs (www.sara.gov.cn) records geographic information about all existing religious institutions in China. We use a Python program to crawl geographic information about Buddhism temples from the website.

We measure the strength of clan culture in a city by the total number of genealogies (Greif & Tabellini 2010, 2017; Chen *et al.* 2022). A clan is a kin-based organization whose members share a common surname and a common patrilineal progenitor. Since genealogy compilation is an essential part of a clan's activities, the number of genealogies in a city is a desirable proxy variable for the strength of local clan culture (Zhang 2020). We manually collect the genealogy data from the Comprehensive Catalogue of the Chinese Genealogy, which is the most comprehensive collection of Chinese genealogies available.

Digital finance – We use the Digital Inclusive Financial Index (DIFI) to measure digital finance development. It is jointly compiled by the Digital Finance Research Center of Peking University and Ant Financial Service (Guo *et al.* 2020). The city-level DIFI provides a description of the digital finance development in China between 2011 and 2019.

Leader turnovers – We manually collect information on local officials (municipal secretaries and mayors) who served in Chinese cities between 2011 and 2019. The data sources include the China Yearbook of Municipalities, provincial yearbooks, and government websites.

City-level macroeconomic variables – We obtain city-level macroeconomic data from the China City Statistical Yearbook. These data include GDP, employment, land area, government expenditure and revenue, the number of schools, the number of hospitals, and the mobile phone penetration rate (i.e. the number of mobile phones per person). We replace the missing values of the macroeconomic variables with the values of the previous years for each city.

Table 1 compares the macroeconomic variables of pilot and nonpilot cities in 2011. Pilot and nonpilot cities had no obvious differences in the air pollutant emissions, the natural population growth rate, the logarithm of the number of hospitals, the logarithm of the number of schools, and the mobile phone penetration rate. However, pilot and nonpilot cities showed significant differences in terms of the logarithm of GDP, the logarithm of government expenditure, the proportion of employees in the secondary industry, and the proportion of employees in the tertiary industry.

Sample selection – We impose several sample restrictions in our empirical analysis. First, we exclude households residing in rural areas (Li & Wu 2014; Chu & Wen 2019; Ma *et al.* 2019). The concept of entrepreneurship in rural areas is not well defined because rural

households in China typically engage in low-skilled self-employment activities such as farming, fishery, and other agricultural production activities (Ma *et al.* 2019). Second, we exclude households whose household heads are aged below 18 or above 55. Age 18 is the age of majority and age 55 is the retirement age for female employees working in tech-related positions in China. Third, we restrict the cities to those surveyed at least four times. This restriction ensures that each city appeared in both pre- and post-program periods. Fourth, we restrict the households to those surveyed twice or more because our baseline econometric specification includes household fixed effects. Finally, we obtain a sample of 32,048 observations from 12,112 households. To mitigate the influence of outliers, we conduct one percent winsorization of the financial variables (entrepreneurial investment, revenue, and profit) and the number of informal institutions.

Table 2 presents descriptive statistics for the main variables used in our analysis. Because of data availability, the number of observations for the regression analysis may vary with outcome variables. About 27.1% of the household heads are female, 89.0% are married, and the average age is 42.31 years. The proportion of households operating businesses is about 22.0%, which is in line with the previous literature on entrepreneurship in China (Li & Wu 2014). About 15.5% of households are affected by the CDCC program during the sample period.

3.2 Empirical strategy

Our empirical analysis uses a DID strategy. Specifically, we estimate the following empirical model:

$$Y_{ict} = \beta_0 + \beta_1 \times CDCC_{ct} + X_{ict}\gamma + t \times Z_c\theta + \delta_i + \alpha_c + \lambda_t + \epsilon_{ict} \quad (1)$$

where i, c, and t represent household, city, and year, respectively. Y represents the outcomes of interest, including entrepreneurship and the logarithm of entrepreneurial investment. $CDCC_{ct}$ is an indicator variable for the implementation of the CDCC program in city c at year t. X_{ict} stands for time-varying household characteristics, including the household head's age, marital status, hukou type, and community membership. δ_i represents household fixed effects that account for any unobserved time-invariant household characteristics determining entrepreneurial activities. The inclusion of the household fixed effects allows us to examine the changes in entrepreneurial activities within households due to the CDCC program. α_c refers to city fixed effects that account for any unobserved time-invariant city-level determinants of entrepreneurial activities, such as traditional culture, social norms, and geography. The city dummies can not be absorbed by the household fixed effects because the households may migrate across cities. λ_t indicates year fixed effects, which control for time-varying factors that are constant across cities. These factors may include national tax and financial policies.

$t \times Z_c$ represents interaction terms between survey year and city characteristics observed in the base year. The interaction terms allow for time-varying effects of predetermined city characteristics on entrepreneurial activities. ϵ_{ict} is a random error term. We use robust standard errors clustered at the city level to correct for possible correlations within cities.

The parameter β_1 is the point estimate of interest, which represents the effects of the CDCC program on entrepreneurial activities. The key assumption of our identification strategy is that in absence of the CDCC program, the entrepreneurial activities in the pilot cities and nonpilot cities would follow parallel trends.

4 Estimation results

4.1 Baseline results

Columns (1) and (3) of Table 3 present the baseline estimation results for entrepreneurial activities. The estimates indicate that the CDCC program significantly promoted entrepreneurship and entrepreneurial investment. Specifically, the CDCC program increased the probability of entrepreneurship by 2.4% and entrepreneurial investment by 10.9%. The regressions in Columns (2) and (4) of Table 3 additionally control for time-varying household characteristics, including household heads' age, marital status, hukou type, and communist party membership. The estimation results remain quantitatively identical. The effects identified in this study are economically significant, given that the annual growth rates of the number and total assets of private enterprises are 17.5% and 14.2% each year during the sample period, respectively.[1]

We then perform a number of robustness checks to address potential identification concerns, including the violation of parallel trends assumptions, the omitted variable problem associated with concurrent macroeconomic shocks, and the sample selection issue. Generally speaking, our estimation results remain robust and we present these results in the appendix.

Parallel trends — In a DID model, the validity of the DID estimates hinges on the parallel trends assumption. Specifically, our estimation of the treatment effect is valid only if changes in the entrepreneurial activities would remain constant over time in both pilot and non-pilot cities in the absence of the CDCC program. In other words, pilot cities should not have experienced improvements in entrepreneurial activities due to differences in time trends prior

[1] In our reporting of the estimation results, we have consistently used three decimal places. Although there are slight variations in the R-squared values across different specifications, these changes are negligible, amounting to less than 0.001. For example, in Column (1) of Table 3, the R-squared is reported as 0.7258, while it is 0.7260 in Column (2) when controlling for other household characteristics. There are two main factors contributing to these minimal changes. First, our model effectively accounts for individual fixed effects, which capture a significant portion of the household-level variations in entrepreneurial activities. Second, some of the additional control variables have small and statistically insignificant coefficients.

to the CDCC program. We adopt four approaches to validate the parallel trends assumptions.

First, we adopt a flexible event-study framework to test for a common pre-trend. The specification is as follows:

$$Y_{ict} = \beta_0 + \sum_{k \neq 0} \rho_k \cdot CDC_{ct}^{k} + \delta_i + \alpha_c + \lambda_t + \epsilon_{ict} \quad (2)$$

where CDC_{ct}^{k} is an indicator for being 2k and 2k-1 years after the implementation of the CDCC program. Specifically, CDC_{ct}^{-2} represents four to five years prior to the program, CDC_{ct}^{-1} represents two to three years prior to the program, CDC_{ct}^{1} represents one to two years after the program, and CDC_{ct}^{2} represents three to four years after the program. We group two adjacent years together because the CHFS is conducted biennially. Other control variables include household, city, and year fixed effects. The omitted reference group is the year when or one year before the CDCC program was implemented. This specification enables us to estimate the dynamic effects of the CDCC program on entrepreneurial activities before and after the pilot city implemented the CDCC program.

Figure A1 illustrates the estimation results for entrepreneurial rate and investment. The estimated coefficients are statistically insignificant in the pre-program period. However, the estimated coefficients become statistically significant and greater in magnitude after the implementation of the CDCC program. The results confirm that the trends of entrepreneurial rate and investment in pilot and non-pilot cities were comparable prior to the program and that considerable differences emerged after the program was adopted.

Second, we examine whether the trends in other irrelevant outcomes remained similar between pilot and non-pilot cities during the sample period. Specifically, we examine the effects of the CDCC program on several time-varying demographic outcomes, including urban hukou status, communist party membership, marital status, and total years of education. As the CDCC program was designed to improve the credit information market outcomes rather than these demographic outcomes, we expect minimal treatment effects on these irrelevant outcomes. Table A3 shows the estimation results. Consistent with our expectations, the estimated coefficients are all small and statistically insignificant. Therefore, we conclude that the demographic outcomes for the pilot and non-pilot cities followed parallel trends.

Third, we allow the trends of entrepreneurial activities to vary with predetermined city characteristics. We add the interaction terms between survey year and city characteristics which were significantly different between pilot and non-pilot cities in the pre-program period. These city characteristics include the logarithm of GDP, the proportion of employees in the secondary industry, the proportion of employees in the tertiary industry, and the logarithm of government

expenditure. Table A4 show the estimation results. The dependent variables in Columns (1) and (2) are the dummy variable for entrepreneurship and the logarithm of entrepreneurial investment, respectively. The results are robust when we control for differential trends associated with predetermined city characteristics.

Finally, we perform a permutation test to examine the possibility of spurious regression. We first randomly select 41 cities as pseudo-pilot for the CDCC program, with the policy implementation time set to 2015 for 11 cities and 2016 for the other 30 cities. We then determine treatment status according to the placebo policy years and estimate the placebo treatment effect using the baseline specification. We repeat this exercise 1,000 times and plot the distributions of the placebo treatment effects in Figure A2. The distributions of the estimated placebo treatment effects are approximately normal and centered around zero, which are significantly different from the actual effects of the CDCC program.

Other simultaneous economic shocks — We examine whether the estimated effects of the CDCC program are confounded by other simultaneous economic shocks. Several economic or policy shocks might also influence entrepreneurial activities during the sample period.

First, we examine the impact of the Business Registration Reform (Shangshi Zhidu Gaige). The reform aimed to encourage entrepreneurial activities by simplifying firm registration procedures, relaxing registered capital requirements, and eliminating the registration and approval of business scope (Barwick *et al.* 2022). The reform was initiated by the State Administration of Industry and Commerce in 2012 as a pilot program in two cities in Guangdong province: Dongguan and Foshan. After the successful pilot, the reform was gradually extended to 10 other cities in Guangdong province before being rolled out nationwide in March 2014. We obtain the data on the timing of the Business Registration Reform from Barwick *et al.* (2022). The timing of the reform approximates the timing of the CDCC program. Furthermore, Guangdong province played an active role in piloting both the CDCC program and the Business Registration Reform, which could confound the estimated effects of the CDCC program.

To address this problem, we control for a dummy variable for the implementation of the Business Registration Reform. Column (1) of Table A5 shows the corresponding estimation results. The dependent variables in Panels A and B are the dummy variable for entrepreneurship and the logarithm of entrepreneurial investment, respectively. The estimated coefficients on the CDCC program remain quantitatively similar. The estimated effects of the Business Registration Reform are positive but statistically insignificant. One potential explanation is that the Business Registration Reform expanded rapidly to the nationwide level, and the immediate

effects may not have been captured due to the biennial nature of the CHFS survey.

Second, we investigate the influence of the "Three-in-One License" Registration System Reform. The Three-in-One License Registration Reform is a further step of the Business Registration Reform. Previously, companies had to obtain three different licenses, namely the business license, organization code certificate, and tax registration certificate. However, after the reform, the government streamlined these three licenses into a single unified business license, making the registration process more straightforward and reducing administrative burden for businesses. The government piloted the reform in several cities in 2014 before implementing it nationwide in 2015. We collect information on the timing of the "Three-in-One License" Registration System Reform from local government websites.[2] The CDCC program was also implemented during 2015–2016. If the implementation of the CDCC program was correlated with the implementation of the "Three-in-One License" Registration System Reform, the estimated treatment effects may be biased.

To address this problem, we control for a dummy variable for the implementation of the "Three-in-One License" Business Registration Reform. Column (2) of Table A5 shows the corresponding estimation results. Similar to the previous analysis, the estimated coefficients on the CDCC program remain quantitatively similar, while the estimated effects of the "Three-in-One License" Registration Reform are statistically insignificant. One potential explanation is that these policies quickly expanded nationwide, and the immediate effects may not have been captured due to the biennial nature of the CHFS survey.

Third, we investigate the impact of the E-commerce Demonstration City program. Launched in 2009, the program aimed to foster e-commerce and promote economic growth in China. From 2009 to 2017, 70 pilot cities were selected successively to experiment with the program. The initiative sought to transform traditional cities into e-commerce hubs by improving logistics and information infrastructure, fostering the growth of e-commerce businesses, and creating favorable policies to support online commerce (Cao *et al.* 2021). To address the potential confounding effect of the E-commerce Demonstration City program, we introduce a control variable by including a dummy variable for its implementation and examine its influence on the estimated coefficients for the CDCC program. The results, presented in Column (3) of Table A5, reveal that the estimated coefficients for the CDCC program remain robust to the inclusion of the control variable.

Fourth, we examine the impact of digital finance. Over the past decade, digital finance has

[2] The pilot cities include Chuzhou, Chenzhou, Yongzhou, Shenyang, Anshan, Chaoyang, Suqian, Taizhou, Suzhou, Fangchenggang, Nanning, Hengshui, Qinhuangdao, Tangshan, Cangzhou, Huzhou, Nanchang, Jiujiang, Ganzhou, Yichun, Shangrao, Ji'an, Fuzhou, Baotou, Ordos, Chifeng, Beijing, Qingdao, and Zhangzhou.

developed rapidly in mainland China. Digital finance may promote entrepreneurial activities by extending the coverage of financial services and lowering transaction costs (Li *et al.* 2021b). If the pilot cities of the CDCC program also made more investments in digital finance infrastructure during the sample period, the estimated treatment effects may be biased without controlling for the effect of digital finance. To tackle this potential threat, we add the city-level DIFI to our baseline specification. The DIFI is widely used in the literature to measure digital finance in China (Guo *et al.* 2020). Column (4) of Table A5 shows the corresponding estimation results. The estimated coefficients on the CDCC program remain quantitatively similar. Therefore, the estimated effects of the CDCC program are not biased by the development of digital finance.

Fifth, we investigate the impact of government leadership turnovers. Government officials can play a significant role in local economic growth. The turnovers of government officials may induce economic fluctuations and affect entrepreneurial activities (Li & Zhou 2005; Yao & Zhang 2015). If the implementation of the CDCC program was accompanied by municipal leader turnovers, our DID estimates may also partially capture the effects of municipal leader turnovers. To address this identification threat, we control for the cumulative turnovers of municipal party secretaries and mayors since 2011. Column (5) of Table A5 reports the corresponding estimation results. We continue to find that the CDCC program had significant positive effects on entrepreneurial activities. Therefore, the turnovers of local leaders are unlikely to bias our results.

Sample selection — First, there is a question of whether the inclusion of first-tier cities causes biases in the estimation results. The first-tier cities in China are Beijing, Shanghai, Guangzhou, and Shenzhen. These cities are large and densely populated and have a profound influence on the country's economy, culture, and politics (Au & Henderson 2006). These cities are more likely to pilot economic reforms due to their economic and political advantages. In fact, all of these cities were selected as the pilot cities of the CDCC program in 2016. If the first-tier cities did not have similar trends in entrepreneurial activities to the non-pilot cities in the absence of the CDCC program, our estimates may be biased. For example, entrepreneurial activities in the first-tier cities might have increased more rapidly than in other cities due to advanced infrastructures and secured business environments. To address this issue, we drop the four first-tier cities from our analysis. The estimates reported in Column (1) of Table A6 are quantitatively similar to the baseline estimates. Therefore, the results are not sensitive to the exclusion of the first-tier cities.

Second, one may doubt whether population migration confounds our estimation results. It

is generally agreed that migrants are more likely to become entrepreneurs than natives (Azoulay *et al.* 2022). If the pilot cities had better infrastructures and attracted more immigrants during the sample period, our estimates may be biased. In Table A3, we have shown the composition of the population did not change significantly due to the CDCC program, suggesting minimal biases associated with population changes. To further address the concern for migration, we exclude migrants from our samples. Column (2) of Table A6 reports the estimation results from the restricted sample. Our estimates vary little across specifications, which increases the confidence in our identification strategy.

Third, there may be a potential sample selection problem when using the pilot as a quasi-experiment in the DID setting. To determine the causal effect of the CDCC program, we use all non-pilot cities as the control group in the baseline analysis. However, incorrect specifications of regression functional forms and non-overlapping distributions of macroeconomic variables in pilot and non-pilot cities may lead to incorrect estimates of missing counterfactual outcomes and treatment effects. To address this incomparability issue, we use a matching DID approach (Heckman *et al.* 1997; Blundell & Dias 2009). We match pilot and non-pilot cities based on macroeconomic variables using nearest neighbor propensity score matching and then conduct DID estimation on the matched sample. The matching variables include the logarithm of GDP, the proportion of employees in the secondary industry, the proportion of employees in the tertiary industry, the logarithm of government expenditure, the logarithm of the number of schools, the logarithm of the number of hospitals, the logarithm of Nitrogen oxides emissions, the logarithm of Sulfur dioxide emissions, the logarithm of industrial dust emissions, the mobile phone penetration rate, and the natural population growth rate. Figure A3 displays the balance of macroeconomic variables before and after propensity score matching. After matching, all macroeconomic variables are well-balanced. Column (3) of Table A6 reports the DID estimates based on the matched sample, and the results show that the CDCC program significantly promoted entrepreneurship and entrepreneurial investment.

Fourth, one may be concerned that excluding the rural sample could lead to biased estimation. To investigate whether the CDCC program's effects differ between rural and urban areas, we include the rural sample and re-estimate the baseline model. The results are reported in Column (4) of Table A6, which indicate that the CDCC program still promotes

entrepreneurship and entrepreneurial investment. We note that low-skilled self-employment activities in the agricultural sector are typically focused on subsistence and survival rather than creating new businesses and industries (Faggio & Silva 2014). Thus, we do not classify self-employment activities in the agricultural sector as entrepreneurship and re-estimate the model using the pooled sample. Column (5) of Table A6 presents the estimation results, which remain qualitatively similar to the baseline model.

Fifth, one may doubt whether administrative ranks bias our estimation results. Pilot cities are more likely to be provincial capitals, which may have better ex-ante credit formal institutions. If these cities had a higher growth rate of entrepreneurship even without the CDCC programs, our estimates would be biased. To address this potential threat, we categorize cities into three groups based on their administrative ranks: provincial-level cities, provincial capital cities, and others. Then, we add the interaction terms between the dummy variables for city groups with different administrative ranks and survey year. The corresponding estimates are reported in Column (6) of Table A6, and our results remain robust.

Staggered DID — Our research design leverages the staggered implementation of the CDCC program. However, there is a recent consensus in the applied econometrics literature that the staggered DID model may be vulnerable to a negative weight problem (De Chaisemartin & d'Haultfoeuille 2020; Callaway & Sant'Anna 2021). The reason behind this is that staggered DID can be interpreted as a weighted average of two-period DIDs, and the treatment effect may vary across different groups and time periods, leading to negative weights (De Chaisemartin & d'Haultfoeuille 2020). Negative weights may result in biased estimates and standard errors that are difficult to interpret. To address this issue, we use the more robust estimates proposed by (Borusyak *et al.* 2021). The key concept of this approach is to estimate the potential outcomes for the treated units using data for the untreated units. We present the results in Table A7, and they are found to be similar to the baseline estimates. Therefore, we conclude that the negative weight issue in our model does not affect the validity of our results.

4.2 Potential mechanisms

The above analysis illustrates that improved credit information arrangements can be conducive to entrepreneurship. In this subsection, we investigate how the CDCC program affected entrepreneurial activities.

We begin by discussing the two major channels through which the CDCC program affected

entrepreneurial activities. First, the CDCC program might alleviate entrepreneurs' credit constraints by increasing the sources of entrepreneurs' funding and decreasing the interest rates of entrepreneurs' debts. For example, Xinyi Credit is a third-party online financial service platform strongly supported by the local governments of the pilot cities after the CDCC program. There are thousands of formal lending institutions such as banks, guarantee companies, pawn companies, and small loan companies on the platform of Xinyi Credit. With information provided by public credit sharing platforms, Xinyi Credit is able to offer loans to small and medium-sized businesses that are suitable for their needs. Another example is the Gongxin E-loan, which is developed by the Industrial and Commercial Bank of China and supported by government agencies of pilot cities. Gongxin E-loan allows enterprises with good credit to obtain low-interest, mortgage-free loans.

We formally examine the effects of the CDCC program on entrepreneurs' credit constraints. Column (1) of Table 4 reports the estimate for the interest rate of enterprise loans.[3] The estimate suggests that the CDCC program significantly reduced the interest rate of enterprise loans by 2.365 percentage points, which is about 46.5% of the sample average. The magnitude of this effect is sizable but plausible. Column (2) of Table 4 presents the estimate for the dummy variable for having enterprise loans from banks or other private sectors. The estimate indicates that the CDCC program raised the probability of having enterprise loans by one percentage point, which corresponds to 17.2% of the sample average.

Second, the CDCC program might lower credit default risks in business activities. Since the CHFS survey does not collect data specifically on credit default risks related to business activities, we address this limitation by utilizing data from the CSMAR. Our analysis focuses on the period spanning from 2012 to 2019 and includes firm and year fixed effects as control variables. In Column (1) of Table A8, the dependent variable is a binary indicator of involvement in economic judicial arbitration, which serves as a proxy for measuring a firm's credit default risks. Our results indicate that the CDCC program led to a 2.4 percentage point reduction in the probability of being involved in economic judicial arbitration, which represents approximately 15.4% of the sample average. This finding confirms that the CDCC program significantly reduced credit default risks in business activities.

In Columns (2) to (4) of Table A8, we present the estimated effects of the CDCC program on the BS index for credit default risk, as well as the credit loan ratio and working capital turnover. As mentioned previously, a higher value of the BS index indicates a greater distance

[3] The variable interest rate is only available for households that run a business, have outstanding bank loans, and are willing to report their interest rate. The fixed-effect model also requires entrepreneurs to report their loan interest rate at least twice. These requirements result in a limited number of regression observations.

to default, signifying a lower degree of credit default risk. The estimation results indicate that the CDCC program significantly reduced the credit default risks of firms, increased the credit loan ratio, and accelerated working capital turnover. It is important to note that credit default risk is influenced by a multitude of factors, including both firm-specific characteristics and macroeconomic conditions. Hence, while the estimated coefficients may appear not large in magnitude, they align with our expectations and offer meaningful insights. For instance, the CDCC program is found to increase the BS index by 0.315, representing a 3.1% increase from the sample average.

Additionally, we use the CHFS data to provide some indirect evidence on the mechanism of lowered credit default risks. Column (3) of Table 4 reports the estimate for the dummy variable for having accounts receivable. Accounts receivable refer to the amount owed to a firm due to its provision of goods or services based on credit. As the default risks of business partners or clients decrease, a company may increase its accounts receivable to encourage them to spend more with the company. The estimate indicates that the CDCC program raised the probability of having accounts receivable by 1.7 percentage points, which corresponds to 18.3% of the sample mean. In general, these findings are consistent with the mechanism of lowered credit default risk.

We have demonstrated that the CDCC program stimulated entrepreneurial activities by alleviating entrepreneurs' credit constraints and lowering the risks of running businesses. We then examine the impacts of the CDCC program on several additional entrepreneurial activities, which may also shed light on how the CDCC program worked.

First, we examine whether the effects of the CDCC program vary with the types of business organizations. We distinguish between formal and informal enterprises. Formal enterprises include limited liability companies, individual proprietorship enterprises, and joint ventures, whereas informal businesses refer to those without formal organizations and privately-owned businesses. Compared with informal businesses, formal enterprises usually engage in complicated business relationships and deal with various financial agents (La Porta & Shleifer 2014). The provision of public credit information may reduce the risks of operating in complicated business environments. Therefore, we expect that formal enterprises gained larger benefits from the CDCC program than informal businesses.

The dependent variables in Columns (1) and (2) of Table 5 are the dummy variables for running formal enterprises and informal businesses, respectively. In line with our expectations, the CDCC program significantly increased the probability of running formal enterprises but had almost zero effect on the probability of running informal businesses. This is desirable from an

economic perspective since informal businesses are often characterized by low productivity, low wages, and stagnant growth (La Porta & Shleifer 2014).

Second, we investigate whether the effects of the program depend upon the size of the firm. Potential entrepreneurs may rely on their own savings or loans from relatives to run small businesses. However, they may find it difficult to solve the financing problem when running large companies (Acs & Virgill 2010). If alleviated financial constraints were an important mechanism driving the effect of the CDCC program, we expect that large companies gained larger benefits from the CDCC program than small companies. We classify the enterprises into two groups based on whether the number of employees is above or below three. The dependent variables in Columns (3) and (4) of Table 5 are the dummy variables for big and small enterprises, respectively. As expected, the CDCC program significantly raised the probability of running big enterprises but had no obvious effect on the probability of running small enterprises.

Third, we investigate whether the CDCC program increased entrepreneurship by encouraging more entries of new firms or by helping existing firms to survive. The CDCC program improved the transparency of credit information, which reduced information asymmetry for all firms, including both new and old ones. However, new entrepreneurs face significant information asymmetry problems due to their lack of business credit history (Kerr & Nanda 2011). This lack of credit history makes it challenging for them to access formal financial institutions that may charge high interest rates, require collateral, or impose strict eligibility criteria. For example, the following webpage (https://qdceloan.com/#/homeIndex) provides information about credit loan products and services in a pilot city named Qingdao, most of which have requirements on years of operation and exclude new entrepreneurs. By contrast, new entrepreneurs may receive more funding support from traditional social networks, such as family, friends, or community members (Kiss & Danis 2008; Adams *et al.* 2014). These networks may be more supportive and encouraging to entrepreneurs who share common values, norms, and expectations but have limited credit information.

Older firms, on the other hand, might benefit more from the CDCC program due to their established credit history and relationships with financial institutions. They might use their credit information to obtain financial support from various economic agents, including formal financial institutions, suppliers, and customers (Bennardo *et al.* 2015). Furthermore, they might experience lower credit default risk when dealing with established clients or business partners. Older firms might provide established clients or business partners with goods on credit to stimulate more consumption or cooperation (Hörner 2002). The public credit information

arrangements might reduce default risks, thereby increasing firm revenue. For instance, the following webpage (https://credit.lanzhou.gov.cn/223/92682.html) cites the example of a small business owner who had previously struggled with late payments and had to borrow money to pay salaries. However, since the introduction of the CDCC program and the publication of the "red-black list" of creditworthy businesses and individuals in their city, the owner has been able to check the list before engaging in business with potential clients, providing them with more security and allowing easier financing.

We divide the enterprises into two groups based on whether the length of operation is below or above three years. The dependent variable in Columns (5) and (6) of Table 5 are the dummy variables for new and old enterprises, respectively. The estimates indicate the CDCC program had no obvious effect on running new businesses but significantly increased the probability of running enterprises that had existed for more than three years.

Finally, we investigate how the CDCC program influenced entrepreneurial revenue and profit. If the public credit information arrangements can reduce credit default risks, it may also extend the depth and scope of transactions and bring about more business opportunities. Therefore, we speculate that entrepreneurs might gain larger revenue and profit due to the CDCC program. The estimates in Table 6 support our speculation. The estimates indicate that the CDCC program raised entrepreneurial revenue by 8.9% and entrepreneurial profit by 7.7%. These results also confirm the rationality of being entrepreneurs after the reform.

4.3 Interactions with informal institutions

Informal institutions refer to a set of social rules that are usually not written but are created, communicated, and enforced outside of official channels or structures (North 1991; Greif 2006). In developing countries where formal institutions such as financial institutions and courts are typically underdeveloped, informal institutions may play a vital role in maintaining business relationships, allocating credits, and reducing transaction risks (Zhang 2020; Miao *et al.* 2021a; Chen *et al.* 2022). A growing body of recent literature has documented that formal and informal institutions may interact and evolve in a complementary way, with mutual feedback (Alesina & Giuliano 2015; Bisin & Verdier 2017). We provide new empirical evidence on this issue by examining the interactions between formal credit information sharing arrangements and traditional informal institutions in China. Specifically, we investigate whether the effects of the CDCC program on entrepreneurial activities increase or decrease with the prevalence of local informal institutions.

First, we examine whether the impacts of the CDCC program depend on the intensity of

Confucian culture. Confucianism is a philosophy and belief system based on the teachings of Confucius and his disciples. It has existed for more than 2,000 years and is concerned with virtue, practical wisdom, and proper social behavior. During the Han Dynasty, the emperor Wu of Han (156 - 87 B.C.) promoted Confucianism as the official ideology and all Chinese feudal states succeeding the Han Dynasty kept this status. Confucian values and norms are still prevalent in modern China and have produced profound impacts on social and economic behavior (Liu *et al.* 2014).

Confucianism typically advocates honesty and credibility in social interaction. For example, Confucius remarked, "One must be a man of his word and resolute in his work… I do not know how a man without truthfulness is to get on." In areas where Confucian culture is highly prevalent, Confucian values may impose strong moral restraints on default behavior and maintain trustworthy behavior in business transactions. As trustworthy behavior has been encouraged even without public credit institutions in these areas, the CDCC program may have a limited impact on opening and managing enterprises.

Following previous studies, we use a city's total number of Confucian temples (divided by 100) to quantify the strength of Confucian culture (Kung & Ma 2014; Miao *et al.* 2021a). We add an interaction term between the dummy for the CDCC program and the number of Confucian temples to examine heterogeneity in the treatment effects of public credit institutions by the intensity of Confucian culture. We do not include the number of Confucian temples in the regressions because it is absorbed by city fixed effects. Columns (1) and (4) of Table 7 show the corresponding estimation results. We find that the CDCC program significantly stimulated entrepreneurial activities in cities without any Confucian temples. However, as the intensity of Confucian culture increases, the effects of the CDCC program on entrepreneurial activities decrease. To get a sense of the interaction effect, consider the following example. If the intensity of Confucian culture increase from the 25th percentile (0.02) to the 75th percentile (0.24), the effects of the CDCC program on entrepreneurship and entrepreneurial investment will decrease by 78.2% and 60.1%, respectively.[4]

Second, we explore whether the effects of the CDCC program depend on religious beliefs. A large body of literature has established that religion is an important social force that shapes entrepreneurial activities (Iyer 2016; Kumar *et al.* 2022).[5] On the one hand, religious networks

[4] Specifically, the effect on entrepreneurship will decrease from 0.047 to 0.010, and the effect on entrepreneurial investment will decrease from 0.173 to 0.068.

[5] Previous studies have produced conflicting results regarding the economic impact of Buddhism. While some studies have found a positive effect of Buddhism on entrepreneurship and firm performance (Lu & Wu 2020; Miao *et al.* 2021b), Wang and Lin (2014) argued that Buddhism had no effect on economic growth. Our results provide new insight that Buddhism may mediate the effect of the CDCC program on entrepreneurship.

can promote the exchange of credit information among people and increase sources of financing for potential entrepreneurs (Lu & Wu 2020). On the other hand, moral obligations imposed by religious beliefs may reduce default behavior in business transactions. In mainland China, Buddhism is the most popular religion and the number of Buddhists is estimated to range from 185 million to 300 million (Xu *et al.* 2021). Buddhism lists dishonesty and lying as one of the "ten evils" and requires Buddhists to practice the precept of "not lying and being honest when speaking". Therefore, potential entrepreneurs in areas with a high prevalence of Buddhism may experience low credit default risks and obtain credit loans even without public credit institutions.

We use a city's total number of Buddhist temples (divided by 100) to quantify the prevalence of Buddhism (Wang & Lin 2014). Again, we use an interaction term to examine whether the effects of the CDCC program vary with the prevalence of Buddhism. Columns (2) and (5) of Table 7 show the estimation results. As expected, the effects of the CDCC program on entrepreneurial activities also decrease with the prevalence of Buddhism. Here is a way to get an idea of the magnitude of the interaction effect. If the prevalence of Buddhism increases from the 25th percentile (0.21) to the 75th percentile (1.52), the effects of the CDCC program on entrepreneurship and entrepreneurial investment will decrease by 21.2% and 15.4%, respectively.

Third, we investigate whether the effects of the CDCC program are heterogeneous across the intensity of clan culture. Clans are kin-based organizations composed of individuals who share a common ancestor and a common surname. Clan-based organizations may play a significant role in maintaining cooperation among members, providing local public goods, regulating interactions with non-members, and coordinating market interactions (Greif & Tabellini 2017; Cao *et al.* 2022). Clan-based networks can facilitate the exchange of credit information and economize on contract enforcement costs within the clans, thereby promoting entrepreneurial activities (Zhang 2020).

We use the total number of genealogies in a city (divided by 100) to quantify the intensity of clan culture (Greif & Tabellini 2010, 2017; Chen *et al.* 2022). Columns (3) and (6) of Table 7 show the corresponding estimation results. We continue to find that the CDCC program promoted entrepreneurial activities. However, the estimated coefficients on the interaction term are small and statistically insignificant, which suggests limited interactions between clan culture and public credit institutions. The lack of interactions may be related to the different target populations. Public credit institutions served the general population and most of their users are strangers. By contrast, clan-based organizations primarily serve acquaintances within the same clan, which only account for a limited proportion of the general population (Greif &

Tabellini 2017).

It is possible that other confounding factors are correlated with the prevalence of informal institutions, which could potentially affect our interpretation of the results. To examine the potential correlation between informal institutions and city-level socioeconomic variables in 2011, we conduct a formal regression analysis. The results of the estimation are reported in Table A9, which shows that informal institutions are significantly associated with various economic factors, such as the logarithm of GDP, the proportion of employees in the secondary and tertiary industries, the logarithm of the number of dishonest judgment debtors, the logarithm of the number of schools, the logarithm of R&D expenditure, and natural population growth rate. To address any possible biases, we include interaction terms between survey year and the socioeconomic variables that are significantly linked to informal institutions in the pre-program period. Table A10 presents the estimation results, which demonstrate the robustness of our findings even after controlling for differential trends that are associated with predetermined socioeconomic variables.[6]

5 Conclusion

This paper provides new empirical evidence on the effects of improved public credit information arrangements on entrepreneurial activities and their interactions with traditional informal institutions. Exploiting the spatial and temporal variations of the CDCC program, we show that the program significantly improved the disclosure of credit information and promoted entrepreneurial activities. Empirical tests suggest that alleviated financial constraints and reduced credit default risks were likely to be potential mechanisms. We also show that the effects of the CDCC program decrease with the prevalence of Confucian culture and Buddhism, suggesting substitution effects between formal credit institutions and informal institutions in promoting entrepreneurship. However, there is little evidence that the effects of the CDCC program vary with the prevalence of clan culture. A possible explanation is that clan-based organizations are generally used by acquaintances within the clan rather than by the general public.

With more complete firm-level datasets and more careful modeling of firm behavior, future studies may further investigate the effects of the CDCC program on other economic outcomes, such as firm productivity, innovation, and export. Understanding these effects of the program may provide important development policy insights for developing and transitioning countries

[6] We agree that our exercise is limited and that future research could benefit from a more carefully crafted research design to investigate this issue further. Nonetheless, we believe that our study provides valuable insights into how the CDCC program worked in different cultural contexts.

lacking credit information sharing arrangements, such as Cameroon, Mozambique, Rwanda, and Sierra Leone. In addition, future studies may investigate how credit information arrangements and other informal institutions such as corruption, political ideology, and culture affect each other and the process of economic development.

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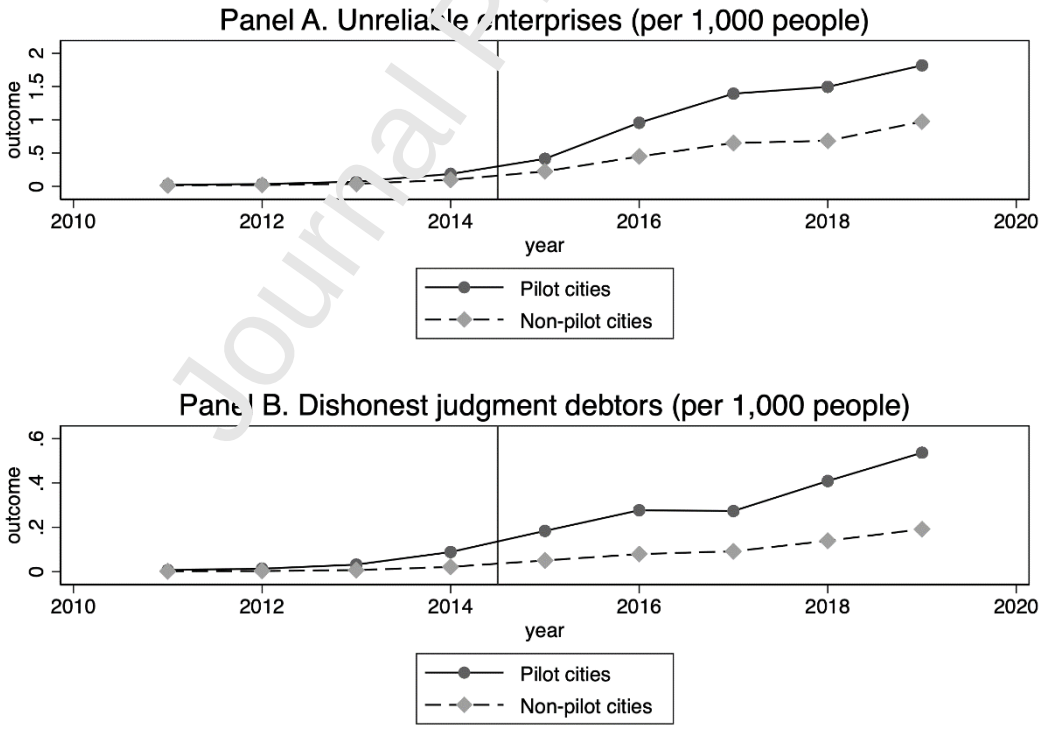

Figure 1 The trends in unreliable enterprises and dishonest judgment debtors

Note: The data on unreliable enterprises and dishonest judgment debtors are crawled from the national credit websites (www.creditchina.gov.cn and www.gsxt.gov.cn). Panels A and B plot the trends in the average numbers of unreliable enterprises and dishonest judgment debtors per 1,000 population, respectively. The solid and dashed lines

represent pilot and nonpilot cities, respectively.

Table 1 Differences in predetermined socioeconomic variables

Variable	(1) Non-pilot cities	(2) Pilot cities	(3) Difference
Log of GDP	16.33	17.16	-0.83***
	(1.10)	(0.95)	(0.18)
Proportion of employees in the secondary industry	42.57	53.79	-11.22***
	(13.90)	(12.84)	(2.31)
Proportion of employees in the tertiary industry	53.83	45.05	8.78***
	(12.80)	(11.86)	(2.12)
Log of government expenditure	13.45	14.48	-1.04***
	(1.18)	(1.19)	(0.20)
Natural population growth rate	5.60	5.86	-0.26
	(3.31)	(4.09)	(0.65)
Log of the number of schools	5.36	5.41	-0.05
	(0.97)	(0.69)	(0.16)
Log of the number of hospitals	5.33	5.20	0.13
	(1.01)	(0.63)	(0.16)
Log of Nitrogen oxides emissions	10.29	10.07	0.22
	(1.37)	(0.86)	(0.22)
Log of Sulfur dioxide emissions	11.592	11.799	-0.206
	（1.51）	（0.85）	(0.24)
Log of industrial dust emissions	10.287	10.070	0.218
	(1.37)	(0.86)	(0.22)
Mobile phone penetration rate	1.053	1.588	-0.535
	(2.21)	(1.84)	(0.35)

Note: Columns (1) and (2) present the means and the standard deviations of the socioeconomic variables in 2011 for the pilot and non-pilot cities respectively. Column (3) presents the differences in the variables between the two groups and the associated standard errors.

Table 2 Summary statistics

Variable	Observation	Mean	Std	Min	Max
Major variables					
Survey year	32,048	2015	2.181	2011	2019
CDCC program	32,048	0.155	0.361	0	1
Entrepreneurship	32,048	0.220	0.414	0	1
Log of entrepreneurial investment	32,048	0.414	1.004	0	11.51
Log of entrepreneurial revenue	32,048	0.389	0.851	0	6.22
Log of entrepreneurial profit	32,048	0.517	1.141	0	7.6
Formal enterprise	32,048	0.028	0.164	0	1

Informal enterprise	32,048	0.208	0.406	0	1
Big enterprises	32,048	0.047	0.211	0	1
Small enterprises	32,048	0.197	0.397	0	1
New enterprise	32,048	0.077	0.266	0	1
Old enterprise	32,048	0.159	0.365	0	1
Entrepreneurial loan	32,048	0.058	0.234	0	1
Accounts receivable	21,899	0.093	0.290	0	1
Bank loan interest rate	622	5.136	3.935	0	17.3
City characteristics					
DIFI index	32,048	188.836	58.575	24.37	321.6
Cumulative turnovers of mayors	32,048	2.032	1.606	0	9
Cumulative turnovers of party secretaries	32,048	1.056	0.847	0	3
Number of genealogies/100	32,048	1.82[illegible]	3.147	0	14.21
Number of Buddhism temples/100	32,048	1.20[illegible]	1.619	0.01	14.35
Number of Confucian temples/100	32,048	[illegible].145	0.129	0	0.72
Household head characteristics					
Age	32,048	42.31	7.957	19	54
Female	32,048	0.271	0.445	0	1
Married	32,048	0.890	0.312	0	1
Communist membership	32,048	0.151	0.358	0	1
Urban hukou	32,048	0.622	0.485	0	1
Years of education	32,048	11.265	3.405	1	16

Table 3 Baseline results

VARIABLES	Entrepreneurship		Entrepreneurial investment	
	(1)	(2)	(3)	(4)
CDCC program	0.024***	0.024***	0.109***	0.109***
	(0.009)	(0.009)	(0.031)	(0.031)
Observations	32,048	32,048	32,048	32,048
R-squared	0.726	0.726	0.661	0.661
Household FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Other controls	NO	YES	NO	YES

Note: The dependent variable in Columns (1) and (2) is the dummy variable for entrepreneurship. The dependent variable in Columns (3) and (4) is the logarithm of one plus entrepreneurial investment. The key independent variable is the dummy variable for the CDCC program. Other control variables include household heads' age, marital status, hukou type, and communist party membership. Standard errors in parentheses are clustered at the city level. ***significant at 1% level, **at 5%, *at 10%.

Table 4 Potential mechanisms

VARIABLES	(1) Enterprise loan interest rate	(2) Enterprise loans (all sources)	(3) Accounts receivable
CDCC program	-2.365*	0.010*	0.017*
	(1.282)	(0.006)	(0.010)
Observations	229	32,048	18,768
R-squared	0.554	0.537	0.684
Household FE	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES

Note: The dependent variables in Columns (1) to (3) are the interest rate of enterprise loans, the dummy variable for having enterprise loans from banks or other private sectors, and the dummy variable for having accounts receivable, respectively. The sample sizes vary across the regressions due to data availability. Standard errors in parentheses are clustered at the city level. ***significant at 1% level, **at 5%, *at 10%.

Table 5 Firm composition

	(1) Formal enterprise	(2) Informal enterprise	(3) Big enterprise	(4) Small enterprise	(5) New enterprise	(6) Old enterprise
CDCC program	0.021***	0.003	0.019***	0.005	0.004	0.020***
	(0.008)	(0.010)	(0.006)	(0.009)	(0.006)	(0.007)
Observations	32,048	32,048	32,048	32,048	32,048	32,048
R-squared	0.580	0.708	0.620	0.700	0.506	0.703
Household FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: The formal enterprise indicator takes a value of one if the household runs a formal enterprise and zero if the household does not run businesses or runs a business without formal organizations. The informal enterprise indicator takes a value of one if the household runs a business without formal organizations and zero if the household does not run businesses or runs a formal enterprise. The indicators for small, big, old, and new enterprises are defined similarly. Standard errors in parentheses are clustered at the city level. ***significant at 1% level, **at 5%, *at 10%.

Table 6 Firm performance

VARIABLES	(1) Entrepreneurial revenue	(2) Entrepreneurial profit
CDCC program	0.089***	0.077***
	(0.028)	(0.025)
Observations	32,048	32,048
R-squared	0.710	0.688
Household FE	YES	YES
City FE	YES	YES
Year FE	YES	YES

Note: The dependent variables in Columns (1) and (2) are the logarithm of one plus entrepreneurial revenue and profit, respectively. Standard errors in parentheses are clustered at the city level. ***significant at 1% level, **at 5%, *at 10%.

Table 7 Interactions between formal and informal institutions

	Entrepreneurship			Entrepreneurial investment		
	(1)	(2)	(3)	(4)	(5)	(6)
CDCC program	0.050***	0.052***	0.028***	0.183***	0.131***	0.113***
	(0.015)	(0.016)	(0.011)	(0.052)	(0.034)	(0.041)
CDCC program *#Confucian temples	-0.166*			-0.480*		
	(0.087)			(0.268)		
CDCC program *#Buddhism temples		-0.005*			-0.015*	
		(0.003)			(0.006)	
CDCC program *#Genealogies			-0.001			-0.001
			(0.003)			(0.009)
Observations	32,048	32,048	32,048	32,048	32,048	32,048
R-squared	0.726	0.726	0.726	0.661	0.661	0.661
Household FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: The dependent variable in Columns (1) to (3) is the dummy variable for entrepreneurship. The dependent variable in Columns (4) to (6) is the log of entrepreneurial investment. We interact the CDCC program indicator and the numbers of Confucian temples, Buddhism temples, and Genealogies (divided by 100). Standard errors in

parentheses are clustered at the city level. *** indicates significance at the 1% level, ** at 5%, and * at 10%.

Appendix

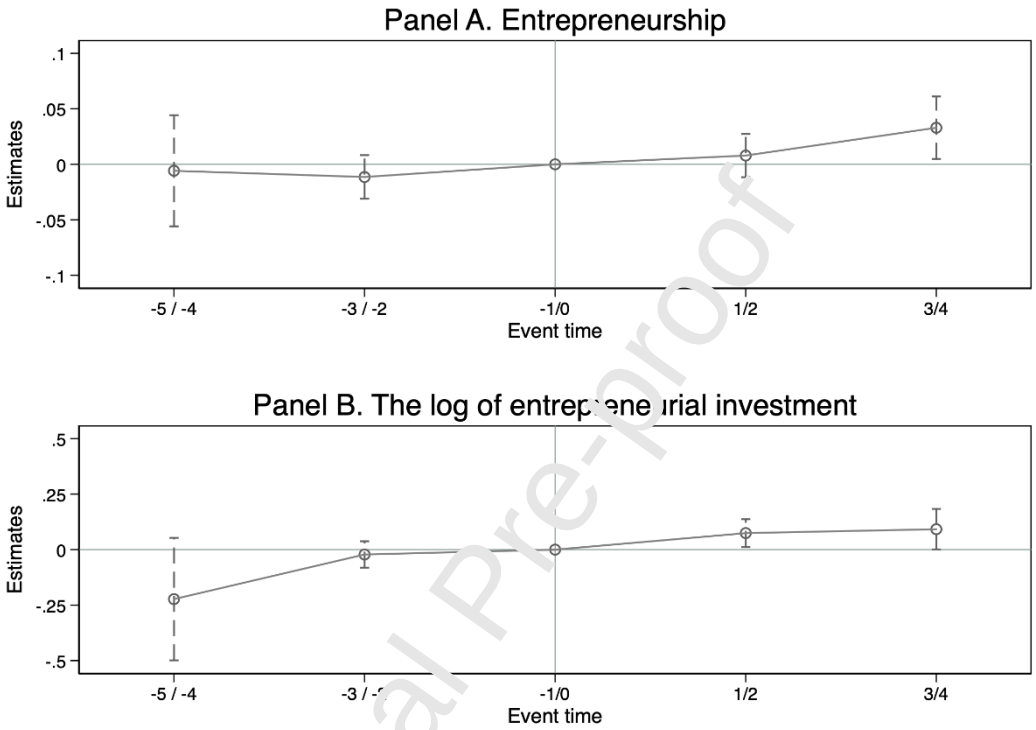

Figure A1 Event analysis

Note: The figure plots event-study estimates of ρ_k for entrepreneurial outcomes using the specification in equation (2). The dependent variables in Panels A and B are the dummy variable for entrepreneurship and the logarithm of entrepreneurial investment, respectively. Event time is defined relative to the time when the CDCC program was implemented. The omitted category is the implementation year of the CDCC program and the year before its implementation. Vertical lines indicate the 90 percent point-wise confidence intervals. The Standard errors in parentheses are clustered at the city level.

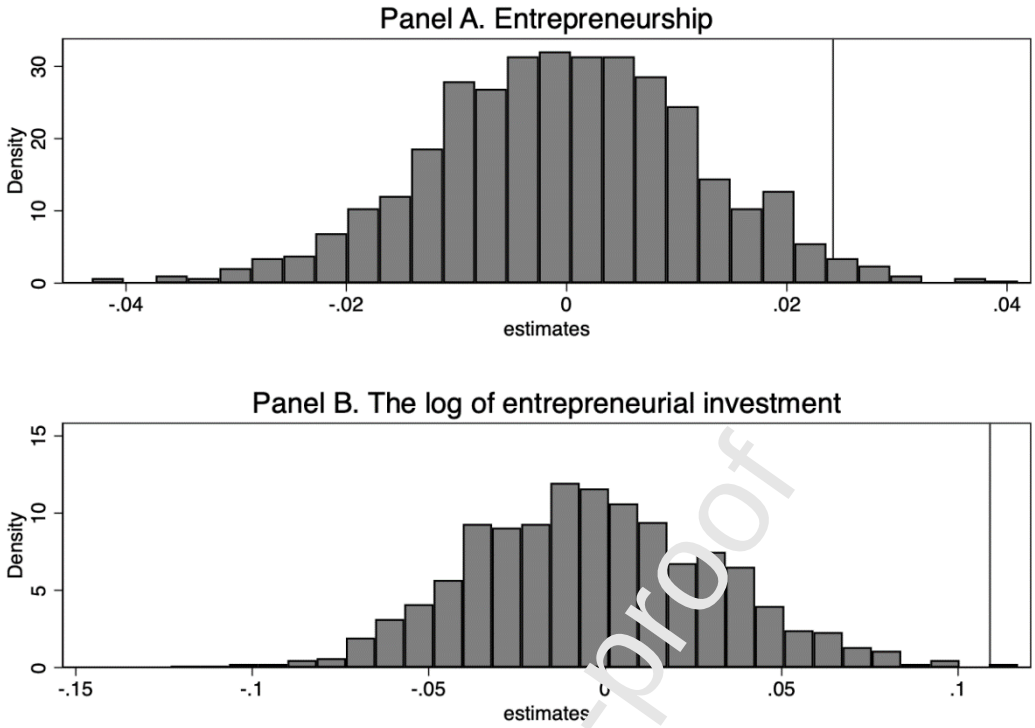

Figure A2 Placebo test

Note: The figure shows the histograms of placebo treatment effects. We randomly assign 11 cities as the first batch of pilot cities (treated in 2015) and assign another 30 cities as the second batch of pilot cities (treated in 2016). We then determine treatment status according to the placebo years and estimate the placebo treatment effect using the baseline specification. We repeat this exercise 1000 times and plot the distributions of the placebo treatment effects. The thick line represents the true treatment effect.

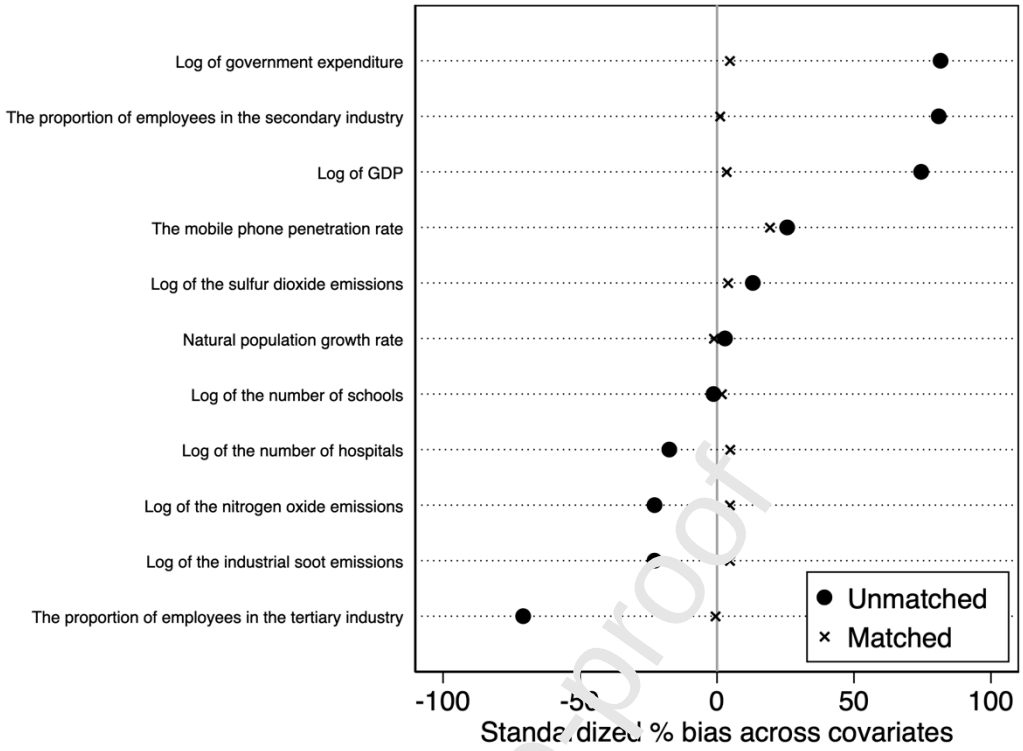

Figure A3 Balance test of macroeconomic variables

Note: The figure shows the balancing of the macroeconomic variables before and after propensity score matching.

Table A1 Pilot cities of the CDCC program

Policy year	Pilot cities
2015	Liaoning Shenyang, Shandong Qingdao, Jiangsu Nanjing, Jiangsu Wuxi, Jiangsu Suqian, Zhejiang Hangzhou, Zhejiang Wenzhou, Zhejiang Yiwu, Anhui Hefei, Anhui Wuhu, Sichuan Chengdu
2016	Beijing, Inner Mongolia Hohhot, Hubei Wuhai, Liaoning Dalian, Liaoning Anshan, Liaoning Liaoyang, Heilongjiang Suifenhe, Shanghai, Jiangsu Suzhou, Zhejiang Taizhou, Anhui Anqing, Anhui Huaibei, Fujian Fuzhou, Fujian Xiamen, Fujian Putian, Shandong Weifang, Shandong Weihai, Shandong Dezhou, Henan Zhengzhou, Henan Nanyang, Hubei Wuhan, Hubei Xianning, Hubei Yichang, Hubei Huangshi, Guandong Guangzhou, Guangdong Shenzhen, Guangdong Zhuhai, Guangdong Shantou, Guangdong Huizhou, Sichuan Luzhou

Table A2 Dishonest judgment debtors and unreliable enterprises

	(1)	(2)
VARIABLES	Dishonest judgment debtors	Unreliable enterprises

CDCC program	0.405***	0.110***
	(0.100)	(0.027)
Observations	3,136	3,136
R-squared	0.621	0.592
Mean of Y	0.410	0.084
Year FE	YES	YES
City FE	YES	YES

Note: The dependent variables in Columns (1) and (2) are the average numbers of unreliable enterprises and dishonest judgment debtors per 1,000 population in pilot and nonpilot cities, respectively. The data are crawled from the national credit websites (www.creditchina.gov.cn and www.gsxt.gov.cn). Standard errors in parentheses are clustered at the city level. ***significant at 1% level, **at 5%, *at 10%.

Table A3 Demographic outcomes

VARIABLES	(1) Urban hukou	(2) Community membership	(3) Married	(4) Years of education
CDCC program	0.006	0.013	0.012	0.039
	(0.009)	(0.015)	(0.009)	(0.048)
Observations	32,048	32,048	32,048	32,048
R-squared	0.776	0.757	0.777	0.910
Household FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Standard errors in parentheses are clustered at the city level. ***significant at 1% level, **at 5%, *at 10%.

Tables A4 Differential trends associated with predetermined city characteristics

	Entrepreneurship	Entrepreneurial investment
	(1)	(2)
CDCC program	0.024**	0.119***
	(0.010)	(0.029)
Logarithm of GDP*Year trend	0.004	0.012
	(0.007)	(0.021)
Proportion of employees in the 2nd industry* Year trend	0.000	0.001
	(0.001)	(0.001)
Proportion of employees in the 3rd industry* Year trend	0.000	0.000
	(0.001)	(0.001)
Logarithm of government expenditure*Year trend	-0.004	-0.015

	(0.005)	(0.016)
Observations	30,748	30,748
R-squared	0.726	0.662
Household FE	YES	YES
City FE	YES	YES
Year FE	YES	YES

Note: The dependent variables in Columns (1) and (2) are the dummy variable for entrepreneurship and the logarithm of entrepreneurial investment, respectively. The regressions control for the interaction terms between survey year and the city-level socioeconomic variables in 2011, including the logarithm of GDP, the proportion of employees in the secondary industry, the proportion of employees in the tertiary industry, and the logarithm of government expenditure. Standard errors in parentheses are clustered at the city level. ***significant at 1% level, **at 5%, *at 10%.

Table A5 Other confounding factors

	Business Registration reform	Three-in-One License	E-commerce Demonstration City	Digital finance	Leader turnovers
	(1)	(2)	(3)	(4)	(5)
Panels A. Entrepreneurship					
CDCC program	0.024***	0.024***	0.024***	0.024***	0.024***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Business Registration Reform	0.010				
	(0.047)				
Three-in-One License Reform		-0.007			
		(0.031)			
E-commerce Demonstration City			-0.001		
			(0.015)		
DIFI index				0.000	
				(0.001)	
Secretary turnovers					0.001
					(0.004)
Mayor turnovers					-0.000
					(0.007)
Observations	32,048	32,048	32,048	32,026	32,048
R-squared	0.726	0.726	0.726	0.726	0.726
Panel B. Entrepreneurial investment					
CDCC program	0.108***	0.109***	0.109***	0.103***	0.111***
	(0.031)	(0.030)	(0.030)	(0.028)	(0.028)
Business Registration Reform	0.158				

	(0.104)				
Three-in-One License Reform		-0.047			
		(0.081)			
E-commerce Demonstration City			0.017		
			(0.037)		
DIFI index				0.002	
				(0.003)	
Secretary turnovers					-0.002
					(0.011)
Mayor turnovers					0.026
					(0.020)
Observations	32,048	32,048	32,048	32,026	32,048
R-squared	0.661	0.661	0.661	0.661	0.661
Household FE	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Note: The dependent variables in Panels A and B are the dummy variable for entrepreneurship and the logarithm of entrepreneurial investment, respectively. Column (1) controls for the dummy variable for the Business Registration Reform. Column (2) controls for the dummy variable for the "Three-in-One License" Registration System Reform. Column (3) controls for the dummy variable for the E-commerce Demonstration City program. Column (4) controls for the DIFI index, which accounts for the development of digital finance. Column (5) controls for the cumulative turnovers of municipal party secretaries and mayors. Standard errors in parentheses are clustered at the city level. ***significant at 1% level, **at 5%, *at 10%.

Table A6 Sample selection

	Excluding first-tier cities	Excluding migrants	Matching DID	Including rural samples	Excluding agricultural activities	Administrative rank
	(1)	(2)	(3)	(4)	(5)	(6)
Panels A. Entrepreneurship						
CDCC program	0.021*	0.027**	0.021**	0.016*	0.017*	0.027***
	(0.012)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)
Provincial-level city						0.002
*Year trend						(0.006)
Provincial capital city						-0.006
*Year trend						(0.007)
Observations	27,845	25,581	26,046	51,041	51,041	32,048
R-squared	0.721	0.724	0.728	0.713	0.711	0.726
Panel B. Entrepreneurial investment						
CDCC program	0.111***	0.085**	0.091***	0.081***	0.084***	0.128***
	(0.028)	(0.034)	(0.026)	(0.028)	(0.028)	(0.031)

Provincial-level city						-0.035*
*Year trend						(0.020)
Provincial capital city						-0.019
*Year trend						(0.024)
Observations	27,845	25,581	26,046	51,041	51,041	32,048
R-squared	0.657	0.657	0.664	0.649	0.647	0.661
Household FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: The dependent variables in Panels A and B are the dummy variable for entrepreneurship and the logarithm of entrepreneurial investment, respectively. Column (1) excludes observations from first-level cities. Column (2) excludes migrants. Column (3) presents the matching DID estimates. Column (4) includes observations from rural areas. Column (5) excludes self-employment activities in the agricultural sector from the definition of entrepreneurship. Column (6) controls for the interaction terms between survey year and the administrative rank indicators. Standard errors in parentheses are clustered at the city level. ***significant at 1% level, **at 5%, *at 10%.

Table A7 Staggered DID model

	(1)	(2)
VARIABLES	Entrepreneurship	Entrepreneurial investment
CDCC program	0.026***	0.115***
	(0.007)	(0.023)
Observations	30,337	30,337
Year FE	YES	YES
Household FE	YES	YES

Note: The table presents the robust staggered DID estimates proposed by Borusyak et al. (2021). The sample size is smaller than the baseline regression because of the exclusion of observations with the "bad comparison" problem. Standard errors in parentheses are clustered at the city level. *** indicates significance at the 1% level, ** at 5%, and * at 10%.

Table A8 Credit default risk

	Economic judicial arbitration	BS index	Credit loan ratio	Working Capital Turnover
	(1)	(2)	(3)	(4)
CDCC program	-0.024**	0.315***	0.021*	0.348**

	(0.012)	(0.116)	(0.011)	(0.175)
Observations	34,224	22,264	12,203	23,439
R squared	0.535	0.600	0.720	0.606
Mean of Y	0.156	10.140	0.485	4.032
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Note: The data are from the CSMAR. The sample period is between 2012 and 2019. The dependent variables in Columns (1) to (4) are the dummy variable for being involved in economic judicial arbitration, the BS index, the credit loan ratio, and the working capital turnover, respectively. As financial information reported in the annual reports of listed companies changes over time, the availability of data for different variables may vary, leading to variations in sample sizes across the analyses. Standard errors in parentheses are clustered at the city level. *** indicates significance at the 1% level, ** at 5%, and * at 10%.

Table A9 Informal institution correlation

	(1)	(2)	(3)
VARIABLES	Genealogies	Buddhism temples	Confucian temples
Log of GDP	1.357**	-0.056	0.020
	(0.551)	(0.299)	(0.017)
Proportion of GDP in the secondary industry	-0.024	0.002	0.000
	(0.029)	(0.018)	(0.001)
Proportion of GDP in the third industry	0.038	0.034	0.000
	(0.035)	(0.022)	(0.001)
Proportion of employees in the secondary industry	0.091***	0.030**	0.002***
	(0.024)	(0.012)	(0.001)
Proportion of employees in the third industry	0.046**	0.002	0.002***
	(0.021)	(0.013)	(0.001)
Log of the number of dishonest judgment debtors	0.912***	0.236**	0.013***
	(0.293)	(0.093)	(0.004)
Log of the number of schools	0.434*	0.413***	0.047***
	(0.222)	(0.117)	(0.007)
Log of government expenditure	-0.290	0.391	0.003
	(0.786)	(0.385)	(0.016)
Log of R&D expenditure	-0.673	-0.860**	-0.014
	(0.637)	(0.410)	(0.017)
Population density	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Natural population growth rate	-0.105**	-0.007	-0.001
	(0.046)	(0.029)	(0.001)
Observations	288	288	288
R-squared	0.192	0.128	0.277

Note: The dependent variable in Columns (1), (2), and (3) is the number of genealogies, the number of Buddhist temples, and the number of Confucian temples, respectively. ***significant at 1% level, **at 5%, *at 10%.

Table A10 Interactions between formal and informal institutions

	Entrepreneurship			Entrepreneurial investment		
	(1)	(2)	(3)	(4)	(5)	(6)
CDCC program	0.056***	0.038***	0.025**	0.179***	0.146***	0.098***
	(0.016)	(0.010)	(0.012)	(0.040)	(0.030)	(0.035)
CDCC program *#Confucian temples	-0.210**			-0.481**		
	(0.089)			(0.225)		
CDCC program *#Buddhism temples		-0.009***			-0.026***	
		(0.002)			(0.007)	
CDCC program *#Genealogies			-0.000			0.002
			(0.003)			(0.009)
Observations	32,048	32,048	32,048	32,048	32,048	32,048
R-squared	0.726	0.726	0.726	0.662	0.662	0.662
Household FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES	YES	YES

Note: The dependent variable in Columns (1) to (3) is the dummy variable for entrepreneurship. The dependent variable in Columns (4) to (6) is the log of entrepreneurial investment. Other controls include interaction terms between survey year and the socioeconomic variables that are significantly linked to informal institutions in the pre-program period. Standard errors in parentheses are clustered at the city level. *** indicates significance at the 1% level, ** at 5%, and * at 10%.

Highlights

1. China's reform used big data to enhance public credit information institutions.
2. Improved public credit institutions promoted entrepreneurial activities.
3. Reduced credit constraints and lowered business risks are potential mechanisms.
4. Informal institutions moderated the effect of public credit institutions.