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Anti-corruption and poverty alleviation: Evidence from China☆

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ABSTRACT

This paper studies how China's recent anti-corruption campaign affects poverty incidence. Employing five waves of the China Family Panel Studies (CFPS) data, we find the (potential) poor households in counties that are more exposed to the anti-corruption campaign are associated with a significantly higher level of income and a consequently lower probability of being in poverty post-campaign. This finding survives a vast array of robustness checks based on alternative model specifications, measures of key variables, and sample selection criteria. We find supportive evidence for three plausible mechanisms behind the poverty-reducing effect of the anti-corruption campaign: improved access to transfer payment, reduced government expropriation, and enhanced formal credit support. However, no evidence indicates that the campaign has increased the provision of public goods. Additional analyses suggest that non-politically connected and low-income households benefit more. Overall, our study offers a novel perspective to shed light on the political economy of poverty alleviation in China.

1. Introduction

Corruption is a significant problem in developing countries and particularly, China has long been plagued by corruption. It has been suggested that corruption lowers economic growth and hampers investment, innovation, and entrepreneurial activities (see e.g., Mauro, 1995; Keefer and Knack, 1997; Wei, 1997; Mo, 2001; Anokhin and Schulze, 2009). However, mostly focusing on the efficiency implications of corruption, the empirical literature has largely overlooked the distributional consequences of corruption, with the exception of several papers using cross-country macro data (see e.g., Gupta et al., 2002; Uslaner, 2008). Corruption is also an important cause of poverty. First of all, theft in redistribution projects directly results in fewer subsidies and transfers received by the poor group (Reinikka and Svensson, 2004; Olken, 2006). Furthermore, corruption acts like a tax and imposes additional costs on businesses—it reduces one's returns to labor effort and investment

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through government expropriation, thus deterring innovation and entrepreneurship. The "grease-the-wheels" hypothesis on corruption (Leff, 1964; Beck and Maher, 1986; Cheung et al., 2012) that bribery may allow firms to get things done in countries with bad institutions does not apply to the poor, who usually cannot afford expensive bribes. Moreover, corruption lowers the efficiency of government provisions of goods and services through price effects and distortions (Olken and Pande, 2012), which may have a greater negative impact on the poor since they are more likely to rely on public goods.

China has achieved remarkable progress in poverty alleviation and combating corruption in the recent decade,[1] both of which are important targets under the United Nations' Sustainable Development Goals (SDGs). Given the important theoretical linkages between corruption and poverty, several interesting questions arise: To what extent can the declining poverty rates be attributed to efforts in combating corruption? Has China's anti-corruption campaign contributed to inclusive economic growth that in turn helps reduce poverty? If so, what are the potential mechanisms? While our study focuses on China by taking advantage of a plausibly exogenous natural experiment—the large-scale anti-corruption campaign, the political economic logic may be applied to other developing nations as well.[2]

China provides an ideal setting to investigate these issues. First, the anti-corruption campaign in China, launched by the Xi Jinping administration, is considered the most far-reaching and lasting than any previous attempts. Largely unanticipated by local governments and households, the launch of the anti-corruption campaign was exogenous to individual income and poverty status. Thus, to measure to what extent corruption hampers family welfare, we explore how the poverty incidence of households living in an *ex ante* more corrupt environment, varies after the start of the campaign, relative to those living in an *ex ante* less corrupt environment. Second, in 2010, the beginning of our sample period, the poverty rate in China was 6.77% (9.41%) based on the World Bank's $1.9 poverty line (2011 China's official poverty line) (Chen and Ravallion, 2021). However, due to the vast size of the Chinese population, the seemingly low poverty rate means that there were still around 100 million Chinese people living in poverty. In addition, given the fact that the unbalanced development across regions as well as between urban and rural areas in China, there exists substantial variation in the levels of poverty rates and corruption geographically, which we will exploit in our identification.

Third, while corruption is notoriously hard to measure (Olken and Pande, 2012), the China Family Panel Studies (CFPS) dataset provides valuable information that can be used to infer local corruption: the individual real experience of encountering bribery, the perception of government corruption severity, and the evaluation of local government performance. Since the county/district government plays an important role in individuals' daily lives and is also the subject of evaluation in the CFPS, we aggregate the above three variables to the county level and consolidate the three county-level variables to generate a single-dimension Regional Corruption Index (*RCI*) using principal component analysis (PCA). The positive and statistically significant association between our RCI and two widely used corruption measures lends confidence to the validity of our proposed corruption measure.

Using five waves of CFPS panel data from 2010 to 2018, we examine whether the anti-corruption campaign has contributed to the reduced poverty incidence in China. We apply a difference-in-differences (DID) identification strategy with a continuous treatment to examine how the income and poverty incidence of the poor households among those living in *ex ante* more corrupt counties changes after the campaign relative to those in *ex ante* less corrupt counties. Using *RCI* to capture the county-level corrupt environment, our empirical result suggests that the negative shock to corruption is associated with a reduction in the poverty incidence of families living in *ex ante* more corrupt environments. We find that a one-standard-deviation increase in the corruption severity (*RCI*) decreases the likelihood of extreme poverty (daily income less than $3.2) by 1.7 percentage points after the anti-corruption campaign, approximately a 3.7 percent decrease for the average poor family. Our results survive a battery of robustness checks, including a parallel trend check, a placebo test, and estimations based on alternative measures of the treatment variable and sample selection criteria. We then investigate the effect heterogeneity and find the non-politically connected families and low-income households benefit more from the campaign. The results further highlight that the anti-corruption campaign could level the playing field by reducing inequality in the earnings distribution for those more exposed to the campaign.

In accounting for the poverty alleviation effect of the anti-corruption campaign, we examine several potential mechanisms. Direct consequences of the crackdown include less theft from public projects by local officials and reduced government expropriation (Olken, 2007; Xu and Yano, 2017). We indeed find stronger exposure to the campaign leads to a larger increase in the business income per capita and in the amount of subsidy and housing demolition compensation received from the government after the anti-corruption. Moreover, since the previous literature confirms the critical role of access to banking services in helping the poor escape the poverty trap (e.g., Burgess et al., 2005; Banerjee et al., 2015; 2019), we then turn to testing the credit channel. Consistent with the fact that China's financial sectors dominated by state-owned banks were notoriously corrupt and also heavily targeted by the anti-corruption campaign, we find the campaign has facilitated households' access to formal credit. Another potential channel could be improved public goods provision. To verify this, we utilize available information on whether a family uses tap water and has constant access to electricity or not, respectively. However, we find null or even negative effects on these two infrastructures. One plausible explanation is that as a result of

[1] On 26 February 2021, President Xi announced that China had achieved the "miracle" of eradicating extreme poverty. According to China's poverty criteria, all 98.99 million poor rural populations have been lifted out of poverty, and the 832 poverty-stricken counties and 128,000 villages have been removed from the poverty list.

[2] For anti-corruption campaigns in other developing countries, see, e.g., Di Tella and Schargrodsky (2003), Olken (2007), Avis et al. (2018) and Sharma et al. (2021).

weakened incentives induced by the campaign (e.g., fewer kickbacks from the public projects), the risk-averse local official may find it optimal to exert less effort to perform her duties, particularly in the provision of infrastructure projects.

This paper contributes to the literature highlighting the improvement of institutions and government performance as means of alleviating poverty. Two approaches have been widely used in the study of poverty alleviation programs: the technocratic approach and the institutional approach (Besley, 1997). While the former emphasizes designing policies that effectively target the poor with a specific focus on the incentive effects, the latter focuses on the role of institutional and political factors. However, led by the Abdul Latif Jameel Poverty Action Lab (J-PAL), most recent studies in the field of anti-poverty have followed the first approach. Indeed, the "thinking small" methodology provides much meaningful guidance for anti-poverty practices, but it pays little attention to how institutions and politics shape poverty, which may be more relevant in authoritarian regimes (Rosenzweig, 2012; Acemoglu and Robinson, 2015). Given the fact that the empirical evidence on the institutional approach remains scarce, this paper attempts to fill this gap in the literature by exploiting a plausibly exogenous shock induced by China's recent large-scale anti-corruption campaign.

Besides, our paper is related to a large and growing body of literature examining the socioeconomic consequences of China's recent anti-corruption campaign that started at the end of 2012. A number of papers document that firms benefited greatly from the anti-corruption campaign. Firms, particularly private, small, and young firms, are found to improve their operating efficiency (Giannetti et al., 2021), invest more in innovation with more patents produced (Xu and Yano, 2017), and gain favorable access to credit (Li et al., 2021) following the campaign. On the other hand, existing studies also find the anti-corruption campaign has reduced the values of political connections, for instance, in terms of access to discounted land (Chen and Kung, 2019) and cheap loans (Li et al., 2021). In contrast to the vast literature focusing on firms, the welfare effect induced by the anti-corruption campaign on individuals is underinvestigated and thus little understood.[3] To the best of our knowledge, this is the first study that systematically investigates the effect of anti-corruption on poverty reduction.

Finally, our study provides a novel analysis on the political economy of China's recent poverty alleviation. For a long time, China's progress on poverty reduction has been attributed to its fast economic growth and unique capacity for redistribution (Yao, 2000; Ravallion and Chen, 2007; Montalvo and Ravallion, 2010). Specifically, the Chinese government has formulated and launched a series of preferential policies to promote the development of the poverty-stricken counties since the mid-1980s,[4] for example, the "8-7 plan" in the 1990s, and more recently, the "war on poverty" program (*tuopin gongjianzhan*) during President Xi's tenure (Park et al., 2002; Meng, 2013; Li et al., 2020). In this paper, we argue that the effectiveness of poverty reduction programs in China has not only relied on the monetary transfer and support, but also worked through the improvement of institutional quality. In addition, some recent studies cast doubts on the authenticity of official statistics on China's poverty rates, which are believed to underestimate the real situation (Zhang et al., 2014; Chen and Ravallion, 2021). Such measurement biases might pose a threat to research using aggregate data, for example, Park et al. (2002) and Meng (2013). However, with survey data, we can avoid such problems and identify the poor more accurately.

The rest of this paper is organized as follows. Section 2 describes the institutional background and theoretical framework. Section 3 presents the data and variables. Section 4 introduces the econometric specifications and presents the empirical results. Section 5 explores the potential channels, namely reduced government expropriation, enlarged access to subsidies, enhanced formal financial support, and improved public goods provision. Section 6 delivers additional discussions on political connections and the distributional effects. Section 7 concludes.

2. Institutional background and theoretical framework

2.1. The massive anti-corruption campaign

While China has carried out drastic economic reforms since 1978, the political institution, by contrast, has remained almost unchanged for a long time. China generally lags behind in the rankings of institutional quality by international standards and has long been plagued by corruption (Allen et al., 2005; Xu, 2011).[5] As one of the central social and political problems, rampant corruption not only intensifies the conflict between the people and government, but also undermines the implementation of various policies formulated by the central government.[6] President Xi has warned on many public occasions that, if left unchecked, corruption would jeopardize the very survival of the party and the country. By combating corruption, he intended to strengthen the legitimacy of the CPC regime as well as public trust in government.[7]

[3] One exception is Sharma et al. (2021), who find Vietnam's anti-corruption campaign has significant positive effects on individuals' mental health.

[4] Poverty-stricken counties, also called the National Poor Counties, were designated by the central government in the late 1980s and early 1990s, according to a mixed set of poverty lines. Poverty-stricken counties have been the target of China's poverty alleviation programs for a long time, and have enjoyed more fiscal transfer payments and preferential policies. See Park et al. (2002) and Meng (2013) for research on this policy.

[5] In 2010, with a "Corruption Perceptions Index" score of 3.5, China ranked 78th in the world, similar to Colombia, El Salvador, and Panama.

[6] In 2015, the third year after the anti-corruption campaign, as an important means of combating corruption, the State Council audited a total of 5.013 billion yuan (about 1.266 billion dollars) in poverty alleviation funds and found that 150 million yuan (about 37 million dollars) was fraudulently claimed or illegally used, among which 60 million yuan was used for alternative purposes other than poverty alleviation, followed by 55 million yuan that was fraudulently claimed. Details can be found in http://www.xinhuanet.com/politics/2016-06/29/c_129101330.htm?isappinstalled=0.

[7] In addition, the massive anti-corruption campaign, launched immediately after Xi took office, also aimed at building authority and consolidating power, sending out a message that emphasizes absolute loyalty to the party and strict obedience to the central government.

Shortly after he assumed office as the general secretary of the Communist Party of China (CPC) during the 18th National Congress of the CPC in late 2012, President Xi Jinping vowed to crack down on "tigers and flies", that is, high-ranking officials and petty civil servants alike. Although combating corruption is always on the agenda of Chinese leaders, Xi's anti-corruption campaign has been considered the most far-reaching and prolonged than any previous attempts. Only one year after the start, approximately 200,000 officials got punished for corruption or abuse of power in 2013 alone. According to the latest data, the Commission for Discipline Inspection (CDI) and procuratorates at all levels filed 3.85 million corruption cases, and 4.09 million officials were investigated and punished from December 2012 to May 2021.[8]

The crackdown on corruption in the grassroots bureaucracy ("flies") has been stressed since the start of the anti-corruption campaign, especially in the poverty alleviation field. Take the recent initiatives as an example. The Central Commission for Discipline Inspection (CCDI) issued the policy document "Working Plan for Special Governance of Corruption and Work Style in Poverty Alleviation from 2018 to 2020" in 2017,[9] which is a "declaration of war" against corruption in poverty alleviation programs. In the same year, the CCDI investigated and punished 1,463 officials from 25 provinces for corruption in the work of poverty alleviation. To alert local officials, the CCDI set up a special section on its official website to expose typical corruption cases.[10] Following the directive of the CCDI, the local CDIs also increased their efforts to crack down on corruption in poverty alleviation projects. As a result, a total of 64,500 officials were investigated and punished in 2017 alone because of their corruption or improper work and lifestyles in the poverty alleviation work (Zhao, 2018).

2.2. How does the anti-corruption campaign affect poverty reduction?

The anti-corruption campaign aims to crack down on corruption, particularly in the form of bribery and theft of public funds. We argue that the anti-corruption campaign could contribute to poverty alleviation in at least the following three aspects. First, the anti-corruption campaign can allow the poor to obtain more aid funds or transfer payments previously stolen by corrupt local officials. For example, Olken (2006) estimates at least 18% of the rice disappeared in a large poverty alleviation program in Indonesia by comparing administrative records with household survey data. Reinikka and Svensson (2004) document that, on average, only 13% of the grants intended for education expenditures from the central government of Uganda were received by the schools. By directly curbing embezzlement and appropriation of aid funds and subsidies, the campaign is expected to reduce poverty incidence.

Second, corruption acts like a regressive income tax, adding to the cost of conducting business. Corruption reduces one's returns to labor effort and investment through government expropriation of private properties. Based on similar reasoning, corruption also deters entrepreneurship by reducing the expected returns from entrepreneurial opportunities with increased uncertainty and transaction costs (Anokhin and Schulze, 2009). In China, where corruption is pervasive and protection for private property rights is weak, corrupt bureaucrats usually have discretion over the nature and amount of harassment and extort bribes. Private businesses are subject to heavy expropriations from the government and are forced to pay high informal levies, extralegal payments, and bribery, to meet various government regulations of business entry and ongoing operations (Du et al., 2015). The situation is even worse for the poor. On the one hand, the amount of bribes charged by corrupt officials may not be afforded by the poor, or at least a non-trivial part of one's income. On the other hand, if the "rules of the game" in a corrupt country are unclear and biased toward the well-connected, the poor may face an additional risk premium in their investment decisions (Gupta et al., 2002). Consistent with this argument, previous studies find that China's anti-corruption campaign has resulted in enhanced profitability and more investment in innovation, particularly among firms prone to expropriation (Xu and Yano, 2017; Giannetti et al., 2021). Kong and Qin (2021) document a sizeable positive effect of the anti-corruption campaign on entrepreneurship.

Third, the anti-corruption campaign may improve the efficiency of credit allocation, increase credit availability, and enhance formal financial support. In the context of China, credit resources intended for poverty alleviation are channeled and operated by state-owned financial institutions. The state-led operation of formal credit resources makes it different from the microfinance popular in other developing countries. However, China's banking sector has long been plagued by corruption. Kickbacks for loan approvals, massive theft by insiders, misuse of funds, and fraud are common in Chinese banks, rural credit cooperatives, and other financial institutions (Chen et al., 2013).[11] Corruption proves to be prevalent both among top executives and at the rank-and-file level in the banking system. Chen et al. (2013) find that bribery plays a more important role in securing loan access than performance, particularly for the loans originated by smaller banks.[12] As an important target of the sweeping anti-corruption campaign, the financial sector has seen the investigations of at least nine "tigers", in-

[8] Specifically, this includes 392 leading cadres at or above the provincial level (*shengbuji*), 22,000 at the prefecture level (*tingjuji*), more than 170,000 at the county level (*xianchuji*), and 616,000 at the section level (*xiangkeji*). Sources: "Important anti-corruption data released", June 28, 2021, People's Daily WeChat Official Account.

[9] From the website of the CCDI: https://www.ccdi.gov.cn/yaowen/201712/t20171215_151309.html.

[10] For example, Wu Yunping, the former party secretary of Nanzhuang Village in Shanxi Province, defrauded 46,000 yuan of poverty reduction funds through misreporting of expenditures and inflated invoices. In March 2018, Wu Yunping was expelled from the party and was investigated for corruption by the local procuratorate. Details can be found in https://www.ccdi.gov.cn/toutiao/201807/t20180711_175467.html.

[11] As an example, 6 top executives of the Henan Rural Credit Cooperatives were convicted of corruption during 2008–2017. See the news report https://www.163.com/dy/article/D3UQ9OO90530QJAL.html for details.

[12] Moreover, in China private firms have great difficulty in obtaining bank loans whereas larger SOEs enjoy better access to bank loans due to the lending bias towards SOEs in the predominately state-owned banking sector, despite their lower productivity (Cull and Xu, 2003; Cull et al., 2009).

cluding the former assistant chairman of the China Banking Regulatory Commission (CBRC) and the former vice president of the Agricultural Bank of China.[13] Given the large magnitude of the anti-corruption crackdown, we expect the campaign can increase credit availability and help ease the financial constraints of poor households. All combined, we thus hypothesize that:

Hypothesis 1. China's anti-corruption campaign may increase the incomes of the poor group and reduce poverty incidence through improved access to transfer payment, reduced government expropriation, and enhanced formal credit support.

Corruption has detrimental effects on the provision of public goods and the delivery of public services, through theft of funds and resource misallocation (Mauro, 1998; Azfar and Gurgur, 2008; Olken and Pande, 2012). Poor people are disproportionately affected since they often rely heavily on these public goods and services. Previous studies have found plentiful evidence on the theft of governments funds in the redistribution schemes or public works projects in developing countries, reflected as the discrepancies, e.g., between official project costs and an independent engineers' estimate of costs in rural road projects (Olken, 2007; 2009) and between the amount disbursed by the central government and the amount actually received by the intended beneficiaries (Reinikka and Svensson, 2004; Olken, 2006). Moreover, Olken (2007) find there were substantial reductions in missing expenditures associated with stronger audit intensity. By penalizing corrupt bureaucrats, the anti-corruption campaign is thus expected to increase both the quantity and quality of public goods.[14]

However, the crackdown on corruption may also undermine the efforts and productivity of bureaucrats in public goods provision for at least two reasons. First, corrupt bureaucrats are expected to spend more public resources on items on which it is easier to levy large bribes and maintain them secret (Shleifer and Vishny, 1993; Mauro, 1998), for example, large infrastructure projects. Thus the campaign might also work the other way around by reducing the officials' expected net benefits from rent-seeking in public projects. Second, as an unintended consequence, the anti-corruption campaign exerts a "chilling effect" on the efforts and productivity of bureaucrats. Wang (2021) points out that since anti-corruption strengthens the enforcement of formal rules and higher-level directives, the "clean" officials become afraid of doing their daily jobs through informal practices that would otherwise help overcome the pathology of formal procedures. Particularly, the work of public good provision often featuring frequent state-business collaboration is prone to anti-corruption probes. Concerns about possible future investigations thus discourage local officials, who are motivated primarily by the desire to avoid risk and ensure political survival under the intense anti-corruption pressure, from exerting efforts to mobilize resources for local economic development (Wang and Yan, 2020). Consequently, bureaucratic slack prevails among officials as a strategic response.[15] More relevantly, the fact that a large amount of poverty alleviation funds remain idle further supports our arguments.[16] Based on the above two opposing predictions, we therefore have:

Hypothesis 2. China's anti-corruption has ambiguous effects on the provision of public goods.

3. Data and variables

The main data source of this study is the China Family Panel Studies (CFPS) survey, which is widely considered to be a nationally representative sample of Chinese communities, families, and individuals due to its large sample size, advanced sampling design, and low refusal rates.[17] The CFPS baseline survey covers 635 communities, 162 counties, and 25 provinces, representing 95 percent of the entire population in contemporary China (Xie, 2012). The individuals are followed up every two years. The CFPS survey collects a wide range of comprehensive information on the demographic and socioeconomic characteristics of families and individuals, such as income, expenditures, education, health, and place of residence. Besides, it also asks the respondents to present subjective evaluations of corruption-related statements that are essential for the analysis in this paper. We use all available five waves of the panel data from CFPS: 2010, 2012, 2014, 2016, and 2018.

3.1. Sample and poverty identification

This paper focuses on the income-enhancing effect and the consequent change in poverty status for the poor group. We restrict the main sample to the households with per capita income below \$6.4/day ($2 \times$ \$3.2/day) in 2010 or 2012, which we define as the *pre-campaign poor household*.[18] Because the previous literature has not provided empirical guidance for the

Li et al. (2021) find the recent anti-corruption investigations in China have resulted in credit reallocation from less productive SOEs to more productive non-SOEs.

[13] See http://www.mzyfz.com/html/1291/2019-06-10/content-1396277.html for more details.

[14] However, the above logic mainly applies to earmarked transfers. This might not be the case for other general-purpose funds, over which local officials may have more discretionary powers.

[15] Most recent empirical studies find that China's anti-corruption campaign lowered the area of land development projects proposed by bureaucrats, reduced revenue collection and environmental regulation, and hindered local economic development (Wang and Yan, 2020; Wang, 2021).

[16] The audit report of the National Audit Office shows that, out of the 5.013 billion yuan of poverty alleviation funds in 40 counties that were randomly audited, 843 million had been idle for more than one year by the end of March 2016, with the longest duration being more than 15 years.

[17] The CFPS uses multistage probability proportional to size sampling (PPS) with implicit stratification to better represent the Chinese society.

[18] Our choice of the sample selection criterion is mainly based on the chronic nature of poverty status. Given the fact that people living around the poverty line, whose incomes prove to be unstable, may fall back into poverty when experiencing certain shocks, previous studies sometimes predict the

Table 1
Main results.

Panel A. Dependent variable: log (household income per capita)					
	(1)	(2)	(3)	(4) rural	(5) urban
RCI × Post	0.044***	0.039***	0.037***	0.038***	0.014
	(0.011)	(0.012)	(0.012)	(0.015)	(0.021)
Target	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.30	0.29	0.29	0.27	0.31
Observations	36240	32377	31588	20463	10809
Panel B. Dependent variable: poverty status with a $3.2 standard					
	(1)	(2)	(3)	(4) rural	(5) urban
RCI × Post	-0.016***	-0.015***	-0.017***	-0.014**	-0.024***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.009)
Target	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.23	0.23	0.24	0.22	0.25
Observations	37408	33498	32689	21166	11218
Panel C. Alternative poverty lines and samples					
	(1)	(2)	(3)	(4)	(5)
RCI × Post	-0.010**	-0.013**	-0.012**	-0.020***	-0.016***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Target	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.22	0.23	0.16	0.21	0.25
Observations	32689	32689	21126	27766	36047

Notes: In panel A, the dependent variable is the (log) household income per capita. In panel B, the dependent variable is an indicator for household income per capita less than $3.2 per day. In panel A and panel B, columns (4)–(5) consider rural and urban residents separately. In panel C, the dependent variables are indicators for household income per capita being less than (a) $5.5/day and 40% of the provincial average household disposable income per capita in columns (1) and (2), and (b) $3.2/day in columns (3)–(5), respectively. In panel C, columns (3)–(5) use the pre-campaign poor sample selected by the criteria of $3.2/day, 1.5×$3.2/day, and 2.5× $3.2/day, respectively. Standard errors clustered at the household level are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

income level needed to escape the poverty trap in China, our choice of the cutoff is based on the stylized facts revealed by the data. We first count the number of observations that are not identified as the *pre-campaign* poor household but fell into poverty in the *post-campaign* period under the $3.2/day criterion, then divided by the full sample size of our data. This deviation rate can be viewed as the measurement error in our identification of the pre-campaign poor households. We repeat this calculation for alternative definitions of the pre-campaign poor sample, with the income cutoff being a multiple of the $3.2/day, i.e., 1.5, 2, and 2.5. Appendix Table A.1 shows the deviation rates and sample sizes under different poverty lines. The standard adopted in this paper ($2 \times \$3.2$/day) results in an error rate of less than 5%, while at the same time effectively avoiding the inclusion of too many irrelevant observations.[19] Unless otherwise stated, the following empirical analyses proceed using this pre-campaign poor household sample. This sample restriction enables us to focus on the campaign's poverty reduction effects for the poor, which are more important and policy-relevant, while purging the potential income effects on

potential chronic poverty status by calculating the "vulnerability to poverty" (Morduch, 1994; McCulloch and Calandrino, 2003; Ward, 2016). In this paper, instead of introducing more parameters needed to be estimated, we address this problem by simply including more potential impoverished people in our sample.

[19] As shown in Appendix Table A.1, doubling the standard from $3.2/day to $6.4/day increases the sample size by 11,563 observations, i.e., about a 50 percent increase. Indeed, there is a tradeoff between precision and relevance in the sample selection. On the one hand, we want to include more families at risk of falling into poverty to increase the precision of our estimates. On the other hand, we have to be selective about the observations to be used to ensure our findings on poverty reduction and the underlying mechanisms indeed stem from the (potentially) poor people. That said, our results are robust to alternative cutoffs in the sample selection, as shown in Panel C of Table 1.

the better-off group.[20] In other words, it ensures our findings on poverty reduction and the underlying mechanisms in this paper indeed stem from the (potentially) poor people.

The main outcome of interest is the poverty status based on different poverty lines. In this regard, our paper adopts the income-based poverty measures, and uses the adjusted yearly household net income per capita from CFPS.[21] Specifically, we employ two kinds of popular criteria in the literature. The first are the $3.2/day and $5.5/day (2011 PPP) poverty lines proposed by the World Bank, which reflect typical national poverty standards in the lower-middle-income countries (LMICs) and upper-middle-income countries (UMICs) (World Bank, 2018). Compared with the $1.9/day international poverty line (IPL), the two new standards can provide better social and economic assessments of basic needs, and identify more people at the bottom of the income distribution in middle-income countries as poor, thus a stricter poverty identification standard.[22] Second, since a nationally unified poverty line may not reflect the regional differences in living costs and levels of economic development, we classify households with less than 40% of the provincial average household disposable income per capita as the relative poor households. This standard is similar to the one based on the European Union's official relative poverty definition in 2001 (World Bank, 2017).[23] We use the 2011 PPP conversion factor data from the World Development Indicators database to convert the poverty thresholds in US dollars to RMB, and then deflate the poverty thresholds to constant 2010 prices using the provincial CPI. All details about various poverty lines are presented in Appendix Table A.2. In this paper, we mainly focus on the results with extreme poverty status defined based on the $3.2/day standard (i.e., the LMIC line) and use other poverty lines in robustness checks.[24]

3.2. Measures of corruption

A big challenge for this paper is how to properly measure the magnitude of corruption at a disaggregated level. Our estimate of corruption is based on both perception-based measures and individual bribery experiences. The perception-based measure, characterized by its good coverage, is the basis of most cross-country corruption indices (Olken and Pande, 2012),[25] making our study more comparable to the large body of work in the related literature. Another reason we choose the perception-based measure is that it provides more variation than the macro-level measurements. For the sake of objectivity, we also supplement our perception-based measure with bribery experiences in our measure of corruption. The potential drawbacks and validation of our method are discussed in detail later.

In the CFPS survey, respondents were presented with statements to elicit individual exposure to and experiences of corruption in the public sector. We choose three variables to capture the relevant information on corruption: *Severity*: the severity of corruption within the government in China ranging from 0 (not severe) to 10 (extremely severe). *Performance*: the evaluation of the performance of the county/district government last year with a score ranging from 1 (good achievement) to 5 (worse than before).[26] *Fee*: a dummy variable indicating whether an individual has ever experienced unreasonable fees charged by a government agency.[27] In view of the potential measurement errors at the individual level, we aggregate these

[20] One possibility is that, as rich people typically run their own businesses and generally benefit greatly from their connections with officials, the anti-corruption campaign may reduce their income by curbing government-business collusion. The effects on income as well as the underlying mechanisms for the rich people are thus very different from those for the poor and this is beyond the scope of our paper.

[21] Taking 2010 as the benchmark year, we use the provincial consumer price index (CPI) to deflate the household income per capita. Data for compilation of the provincial CPI are collected through the consumer price surveys on representative commodities, which have large consumption and representative price changes, under 262 basic headings in 8 categories. The weights of the consumer price indices are determined according to the composition of the consumption expenditures of urban and rural households. Compared to other price indices (e.g., the retail price index), the provincial CPI can better reflect the impact of price changes on the basic living condition and welfare of residents, and is also the only consumer price index available at the subnational level.

[22] According to World Bank (2018), the $1.9/day line is the average of national poverty lines from 15 poorest countries in the world, while the latter two are the median values of the LMIC and UMIC national poverty lines in about 2011, thus more relevant to China.

[23] In 2001, the European Union adopted as its official definition of relative poverty, 60 percent of the median equivalent disposable income. In other countries, the cutoff used is 50 percent of the median, or closer to 40 percent of the mean (World Bank, 2017).

[24] China was not classified as a UMIC by the World Bank until 2012, the third year of our sample period. It should be noted that the $3.2 and $5.5 lines, though sometimes referred to as LMIC and UMIC lines respectively, each can be used in both groups of middle-income countries to offer higher values reflecting assessments of basic needs (World Bank, 2018). Another commonly used poverty line is the national poverty line drawn by the Chinese government—2,300 yuan/year (about $1.69/day at constant 2010 prices). Since this line is way lower than the $3.2/day one, we focus on the latter and our result is robust to the former.

[25] For example, Transparency International's Annual Corruption Perception Index and the World Bank's Control of Corruption Index.

[26] The Chinese government consists of five layers of administration: the central, the provincial level (including autonomous regions and municipalities), the prefectural level, the county level (including municipal districts), and the township level.

[27] We use all of the three variables in the construction of our corruption measure because each of them may partially capture some useful information regarding local corruption. First of all, while *Severity* seems to perfectly fit our research purpose, the corresponding survey question only asks for the general perception of corruption within China, i.e., not necessarily confined to the respondent's county. To the extent that the perception is formed mainly on the basis of local experience and migration is quite limited in our sample, we believe it should mostly reflect the corruption severity at the local level. However, given that media has become an increasingly more important source of information that may affect one's perception, we check whether this variable is significantly associated with media exposure thus potentially invalidating our use of this variable. We divide provinces into two groups based on the median of provincial-level media exposure, measured by newspaper circulation per capita and internet penetration rates, respectively. Reassuringly, we do not find any significant differences between the two groups of provinces in terms of corruption perception. Second, while the survey question involving *Performance* specifically asks the respondents to evaluate their county/district government's performance, it may capture their evaluation on other dimensions besides corruption. Considering that control of corruption is regarded as the major determinant of local government performance and

variables to the county level by taking the average. We have two reasons to focus on corruption at the county level rather than at lower administrative units like the community/village level: on the one hand, the subject of evaluation regarding corruption in the CFPS survey mainly refers to the local county-level government; on the other hand, owing to a series of reforms, especially the national *Tax and Fee Reform* in 2003, the authority and autonomy of village officials have been severely eroded. The operation of village governments is subject to interventions and direct supervision from the county government (Oi et al., 2012; He, 2019; Martinez-Bravo et al., 2022).[28]

To make the most of all the information available, we consolidate the three county-level variables to generate a single-dimension Regional Corruption Index (*RCI*) using principal component analysis (PCA). Since our three measures of corruption are either binary or ordinal variables, we adopt polychoric PCA following the suggestion of Kolenikov and Angeles (2009). In the case of PCA conducted on discrete variables, polychoric PCA is proved to be more reliable than the standard one. Appendix Table A.3 presents the detailed results from polychoric PCA. The factor loadings show desirable signs that are consistent with intuition: the first component is positively associated with all three variables (*Fee, Performance*, and *Severity*). The magnitude of the factor loading is similar across the three variables with the loading of *Performance* being slightly larger than that of the other two. In addition, the first component accounts for approximately 51 percent of the variations, showing a strong explanatory power. Thus, we will use the first component of PCA as a proxy for county-level *RCI*, which is used to measure the intensity of exposure to the anti-corruption campaign. For convenience of interpretation, we standardize the *RCI* (by subtracting the mean and dividing by its standard deviation) and use that as part of our key explanatory variable.

One may be concerned about the validity of the above measure based on self-reported information. First, if there is a random error in the independent variable or a general tendency to underreport corruption, then the estimate will be biased towards zero. Second, unlike cross-sectional data often used in the studies on corruption (Olken, 2009), the household fixed effects in Eq. (1) would control for the constant reporting bias. We also add many time-variant household characteristics, such as average years of education in the family and the health status of the household head, to alleviate measurement errors in corruption correlated with individual characteristics (Olken, 2009). Third, we aggregate individuals' corruption evaluations to the county level by taking the simple average within each county, which can reduce measurement bias caused by individual heterogeneity and alleviate the endogeneity concern as well.

We validate our constructed *RCI* as a good measure of regional corruption severity by comparing it with commonly used proxies for (anti-)corruption in the literature. First, the entertainment and travel costs (ETC) are considered as a good proxy for firm corruption since managers of Chinese firms always use this item to cover considerable expenses spent bribing government officials with fake or inflated receipts (Cai et al., 2011; Xu et al., 2017). We calculate the average ratio of the firm's entertainment and travel cost to sales in a province from the 2005 World Bank Enterprises Survey for China. Second, we use the logged number of convicted high-ranking officials in each province during 2013-17 as an *ex post* validation for *RCI*. High-ranking officials are defined as the officials at the deputy bureau-director level (*tingjuji*) and above.[29] This measure thus reflects the intensity of the crackdown across provinces. We then regress each measure on provincial *RCI* (average county-level *RCI* in a province), controlling for provincial GDP per capita, GDP growth, population as well as the value added of the secondary and tertiary sectors as a share of GDP. Fig. 1 and 2 present the two added variable plots where each residualized measure is plotted against the residualized *RCI*. It shows a significantly positive relationship between the two proxies and our provincial *RCI*. These validation tests therefore lend support to our use of *RCI* as a good proxy for local corruption.

Another concern about the corruption variable is that it may fail to measure the correct amount of exposure if households choose to move across counties that vary in the severity of corruption after the campaign. This movement may bias our estimates if the migration decision is systematically related to both the intensity of exposure to the campaign and the outcomes. To rule out any potential bias caused by immigration, we limit our sample to the households that stayed in the same county throughout our sample period. This exercise excludes 1,385 observations (4.06%).

3.3. China's war on poverty

China's poverty reduction practices feature a clear top-down style. On the one hand, the state-sponsored pattern turns out to be the very root of many problems. Corruption in bureaucracy offsets some positive effects of the poverty alleviation policies, which partly explains why the central government has launched some special actions to combat corruption in the field of poverty alleviation as described in Section 2.1. Besides, Zhang et al. (2014) point out that the manipulation of poverty statistics is another concern in the poverty alleviation practice. On the other hand, the advantages of state-led poverty alleviation are also obvious. Governments, rather than NGOs, are capable of making huge investments in poor areas (see Appendix Fig. A.1) and subsidizing the poor on a large scale. However, the latter may threaten our identification to the extent that the anti-corruption campaign may coincide with other poverty alleviation policies in the sample period, which could have a direct impact on poverty outcomes. We address this concern in the latter part of this subsection.

other aspects of government performance such as dereliction of duty can also be viewed broadly as corruption, the inclusion of this variable is necessary and appropriate.

[28] For example, the financial escrow policy (*"xiang cai xian guan"*) was implemented in many counties, which requires villages to seek permission from the county authorities to access village funds.

[29] The data on the crackdowns are manually collected from the CCDI website and major Chinese news media online. See Xu et al. (2021) for details.

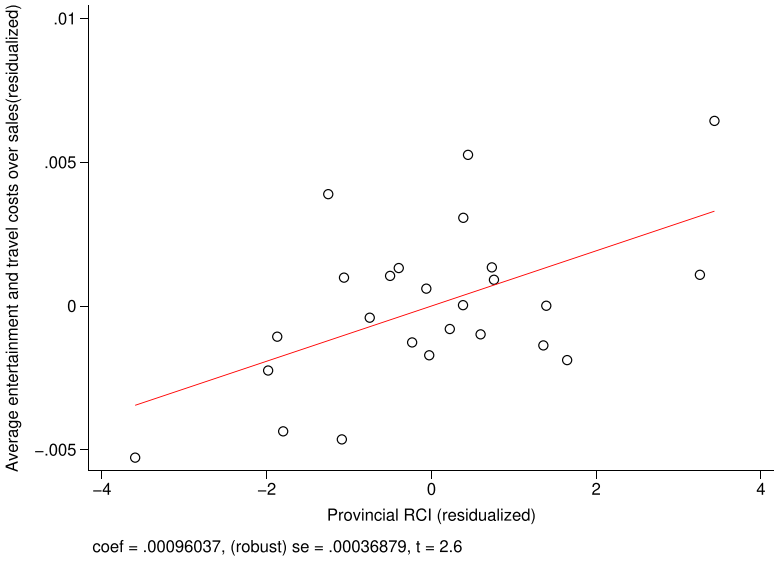

Fig. 1. Partial correlation between ETC and RCI.

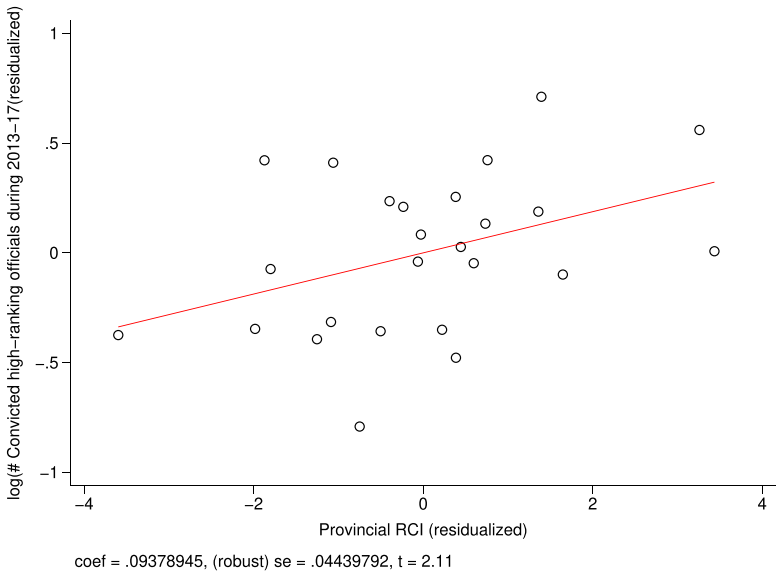

Fig. 2. Partial correlation between log (# Convicted high-ranking officials) and RCI.

The Chinese government implemented a series of preferential policies to promote the development of poverty-stricken counties, which can be traced back to the mid-1980s. The status of poverty-stricken counties designated by the central government is the basis for enjoying these preferential policies. Lifting all 832 poverty-stricken counties out of poverty before 2020 is also an important commitment in President Xi's poverty alleviation plan. We collect data on the list of poverty-stricken counties and the time when these counties were removed from the poverty list from the National Bureau of Rural Development, and control for a dummy variable indicating whether a household lives in a poverty-stricken county in a certain year to account for the county-level heterogeneity in the policy treatment.

Another important event is the "war on poverty" program (*tuopin gongjianzhan*). In November 2015, the Chinese government issued an outline document "Decision of the Central Committee of the Communist Party of China and the State Council on Winning the Battle against Poverty" to guide the work of poverty alleviation from 2016 to 2020, which is generally regarded as the beginning of the "war on poverty" program, a large-scale nationwide poverty alleviation campaign.[30]

[30] Winning the war against poverty was listed as one of the three major tasks in Xi Jinping's report at the 19th CPC National Congress in 2017, showing the extreme importance the CPC has attached to poverty reduction.

At the same time, the number of people lifted out of poverty in the jurisdiction was included as an important criterion in the performance evaluation of local officials at the provincial and county level.[31] Appendix Fig. A.1 presents statistics on the Chinese government's investment in poverty alleviation. We can see that the amount of special poverty alleviation funds received by poverty-stricken counties was low and stable before 2015 but has increased dramatically since then.

In practice, China's recent large-scale poverty alleviation campaign has been guided by the concept of "targeted poverty alleviation" (*jingzhun fupin*), proposed by President Xi in 2013. More specifically, it requires accurately identifying every poor household,[32] and implementing poverty alleviation policies at lower administrative units, e.g., the village. First of all, poverty alleviation funds are eventually distributed to the village committees. These funds include direct subsidies to poor households, as well as funds to promote the upgrading of infrastructures and economic development of the villages. Second, the governments at the county level and above dispatch stationing officials to serve as poverty alleviation cadres in the poor villages, whose duty is to lead villages to shake off poverty through poverty alleviation programs. He and Wang (2017) show the significant role played by the College Graduate Village Officials (CGVOs) program in poverty alleviation in rural areas of China. Third, there are a large variety of poverty alleviation programs, each with a specific focus, for example, Relocation for Poverty Alleviation, Industrial Poverty Alleviation, Tourism Poverty Alleviation, and E-commerce Poverty Alleviation. Most of these poverty alleviation development projects are carried out on a village basis.

Because the village is the basic unit for poverty alleviation programs, we construct a variable $Target_{v,t}$ as the interaction between the pre-campaign village-level poverty incidence in 2012 under China's official poverty line (2,300 yuan at constant 2010 prices) and a year dummy indicating years after 2015. The intuition is that we expect the "war on poverty" program to affect villages with *ex ante* higher poverty incidence to a larger extent. In our empirical design, this variable can be used to further leverage geographic variation in poverty status within the non-poverty-stricken counties and control for the influence of poverty alleviation policies at lower administrative units.

3.4. Control variables

We include several control variables in order to account for the influences of other household-level characteristics. *Urban* is a dichotomous variable that equals 1 if a household's actual place of residence is in town and zero otherwise. *Family size* is defined as the number of members who share the oven within a family. *Number of children* is the number of children under 16 years old. *Education* refers to the average years of education completed by those household members who have finished their education. *Age* is the average age of all household members excluding children.

In addition to family-level characteristics, we also control for the demographic characteristics of the household head.[33] Under the influence of collectivism and patriarchal culture in most Chinese families, the household head, typically the male elder or the one with the best economic position, makes most of the key decisions in the family. *Marriage* is a binary variable indicating whether the household head is married (or having a spouse). *CPC membership* is an indicator of membership of the CPC. Since health is a key determinant of income and also found to be correlated with local corruption (Sharma et al., 2021), we control the self-reported mental health status (*Mental health*) and physical health status (*Physical health*) of the household head. Detailed descriptive statistics on the key variables used in this paper are shown in the Online Appendix Table A.1.

4. Empirical specification and results

4.1. Identification strategy

While the anti-corruption campaign constitutes a nationwide shock, we expect the shock to have affected households living in *ex ante* more corrupt counties/districts to a larger extent. This is because areas that had higher levels of corruption prior to the campaign received relatively greater scrutiny during the anti-corruption campaign, and thus households residing in these areas would potentially benefit more compared to those in regions with lower corruption.[34] Any negative externalities of corruption on poor households should have decreased after 2012, when the campaign started. Empirically, if corruption indeed causes poverty, we should observe that the negative shock to corruption is associated with a positive effect on income and a negative effect on the poverty incidence, especially for households living in *ex ante* more corrupt counties. We thus exploit predetermined variation in the corruption severity (*RCI*) to investigate the effect of the anti-corruption campaign. Similar to Giannetti et al. (2021), we employ a difference-in-differences (DID) identification strategy

[31] On 16 February 2016, the General Office of the Central Committee of the Communist Party of China and the General Office of the State Council issued the "Provincial-level Party Committee and Government Measures for the Evaluation of the Effectiveness of Poverty Alleviation and Development Work". This policy document can be found at http://www.cpad.gov.cn/art/2016/2/17/art_46_45016.html.

[32] Specifically, the process involves the registration and application of a nationally unified poverty identity card for every poor household as the basis for enjoying the poverty alleviation policy.

[33] Following the suggestions of the CFPS dataset center, we define the household head based on questions: "Who is the head of the household?" in the 2010 survey wave, "Who is the primary person in charge of making important decisions (e.g., house construction or purchasing, residential move, children's education, etc.) in your family?" in the 2012 wave, and "For the past 12 months, which family member was most familiar with and could answer the questions on the family's economic conditions?" in 2014–2018 waves.

[34] Colonnelli and Prem (2022) confirm that audits had larger effects in more corrupt areas.

with a continuous treatment variable to investigate the poverty alleviation effect of China's anti-corruption campaign:

$$Y_{i,c,t} = \alpha_1 + \beta_1 RCI_c \times Post_t + \boldsymbol{\lambda}' \boldsymbol{Z_c} \times Post_t + \gamma Target_{v,t} + \phi Poor\ County_{c,t} + \boldsymbol{\xi}' \boldsymbol{X}_{i,c,t} + \theta_i + \mu_t + \varepsilon_{i,c,t} \quad (1)$$

where $Y_{i,c,t}$ is the outcome of our interest, namely the household income per capita and the poverty status for the pre-campaign poor households i residing in county c during year t.[35] $Post_t$ is a dummy variable that takes the value of 1 for years after 2012, i.e., years after the campaign began, and 0 during 2010–2012. We conjecture that households living in more corrupt counties, as captured by the county-level *RCI*, are more exposed to the anti-corruption campaign. To alleviate the confounding effects of omitted factors at the county level, we further control for three county-level variables. First, we include a time-variant dummy variable $Poor\ County_{c,t}$ indicating the status of poverty-stricken counties designated by the central government from the National Bureau of Rural Development. A poor county could be associated with more corruption and at the same time may also receive tremendous fiscal support from the central government, which then in turn impacts the poverty rates. Besides, we also control for each county's initial level of economic development and population in $\boldsymbol{Z_c}$, each interacted with $Post_t$, which alleviates the concern that our findings may just reflect mean reversion. Since the GDP data are subject to manipulation by the local governments in China (Chen et al., 2021) and are missing for a nonnegligible number of counties/districts, we instead use the light emission at night per capita (in logarithm), which is proved to be a reliable proxy for the underlying economic activity (Henderson et al., 2012; Michalopoulos and Papaioannou, 2014).[36] Data on county-level population are derived from the 2010 Population Census. Likewise, to account for the effect of the "war on poverty" program put in place in 2015, we construct the variable $Target_{v,t}$ as the interaction of pre-campaign village-level poverty incidence and a dummy variable indicating years after 2015, i.e., $Target_{v,t} = Poor_v \times Post2015$. We also control for a vector of time-varying household and household head demographics, $\boldsymbol{X}_{i,c,t}$, as described in Section 3.4. θ_i is the household fixed effects to account for household-specific time-invariant characteristics, while μ_t is the time fixed effects, which absorb the secular decline in poverty.

4.2. Main findings

Table 1 shows the main results of this paper. In panel A, we first find a positive correlation between the anti-corruption campaign and income in column (1) without any control variables. In column (2), the coefficient of interest ($RCI \times Post$) changes little when we control for the effect of China's "war on poverty" program (*Target*), which can be attributed to the weak correlation between the two explanatory variables. In order to account for potential confounding factors, we add control variables in our DID regression in column (3), and a robust positive correlation between $RCI \times Post$ and the income still obtains. Quantitatively, a one-standard-deviation increase in corruption severity (*RCI*) implies about a 3.77 (i.e., $e^{0.037} - 1$) percent increase in the household income per capita after the anti-corruption campaign. The interpretation of the finding is that anti-corruption efforts have increased the incomes of people at the bottom of the income distribution. Finally, in view of the large urban-rural gaps in developing countries, we split the families into two subsamples according to their places of residence: urban and rural areas. The subsample analyses in columns (4) and (5) suggest the above effect is mainly driven by the rural residents.

More importantly, we are interested in knowing whether the income-enhancing effect is large enough to change the poverty status. We replace the dependent variables with indicators for poverty status based on various poverty lines: \$3.2 per day in panel B, as well as \$5.5 per day and 40% of the provincial average household disposable income per capita (40% relative poverty line) in panel C. We find a robust negative correlation between $RCI \times Post$ and the poverty incidence still obtains under all the three poverty standards. In our preferred specification (column (3) of panel B), a one-standard-deviation increase in the corruption severity (*RCI*) decreases the likelihood of extreme poverty by around 1.7 percentage points after the anti-corruption campaign. Given a pre-campaign average of 45.4 percent for being in extreme poverty under the \$3.2 per day poverty line among the pre-campaign poor households, this translates into a 3.7 percent decrease for the average sample family. We repeat our estimation of Eq. (1) in column (4) for the rural residents and column (5) for the urban ones, and find a significant poverty reduction effect in both subsamples. In addition, the results in columns (1)–(2) of panel C show that the anti-corruption efforts reduce the poverty incidence under stricter poverty standards—the \$5.5 per day (the UMIC poverty line) and 40% relative poverty lines. Considering that we use the pre-campaign poor household sample with a standard doubling the \$3.2 per day as discussed in Section 3.1, the estimation results in columns (1)–(2) of panel C further boost our confidence in the economic significance of the poverty reduction effect. At last, the results in columns (3)–(5) of panel C confirm that our estimation results are not sensitive to alternative pre-campaign poor samples selected by different poverty lines (i.e., 1, 1.5, and 2.5 times the \$3.2/day line).

We present the detailed results on the full set of control variables in Online Appendix Table A.2. As expected, the estimated coefficients on *Number of children* and *Age* are positive in most specifications, indicating an older family with more

[35] Unless otherwise noted, the empirical results of this paper are all based on the sample of pre-campaign poor households. As discussed in Section 3.1, a pre-campaign poor household is defined as one with a per capita income of less than \$6.4/day in 2010 or 2012.

[36] The nighttime lights data were collected by the U.S. Air Force Defense Meteorological Satellite Program (DMSP) using the Operational Linescan System (OLS) sensors, which report images of the earth at night captured from 20:30 to 22:00 local time. In each satellite-year dataset, the intensity of lights is recorded as a Digital Number (DN) ranging from 0 (no lights) to 63 (top-coded), for every 30 arc-second output pixel (approximately 0.86 square kilometers at the equator) spanning -65° to 75° in latitude and -180° to 180° in longitude. We sum the pixel values within each county in 2012 and then divide it by the county population.

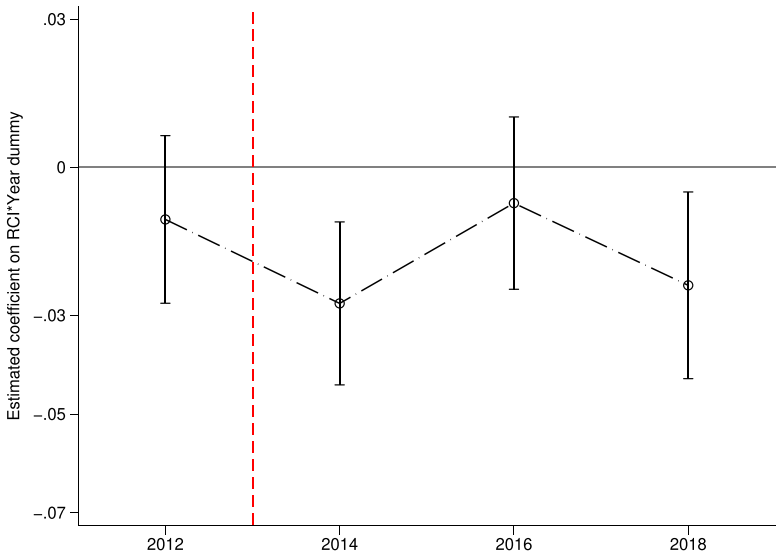

Fig. 3. Test for the parallel trend assumption. *Notes*: This figure presents the estimated coefficients and 95 percent confidence intervals of $RCI_c \times Year_t^m$ in Eq. (2). The red line represents the year when the anti-corruption campaign started. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

children is more likely to fall into poverty, *ceteris paribus*. The positive sign on the linear term of educational attainments coupled with the negative sign on its quadratic term implies decreasing marginal returns to years of schooling. In addition, China's "war on poverty" program turns out to be effective in reducing poverty, as suggested by the negative coefficient on the *Target* variable. Besides, stronger light intensity and more population predict a lower probability of poverty post-campaign. Overall, the signs of most variables are consistent with economic intuition and our prior expectation, which, to a great extent, can help justify our model setup.

4.3. Identification checks

A key identification assumption of the DID approach is that the average trends in poverty incidence are parallel between counties with different corruption severity before the anti-corruption campaign. If there were already differential trends for counties with different levels of corruption before the campaign, the estimates obtained in Table 1 would be biased. To test the validity of the common trend assumption, we replace $RCI \times Post$ in our baseline specification with *RCI* interacted with a dummy variable for each individual year as follows:

$$Poor_{i,c,t} = \alpha_1 + \sum_{m=2012}^{2018} \beta_m RCI_c \times Year_t^m + \boldsymbol{\lambda}' \boldsymbol{Z}_c \times Post_t + \gamma Target_{v,t} + \phi Poor\ County_{c,t} + \boldsymbol{\xi}' \boldsymbol{X}_{i,c,t} + \theta_i + \mu_t + \delta_p \times \mu_t + \varepsilon_{i,c,t} \quad (2)$$

where $Year_t^m$ takes the value 1 if m equals t and 0 otherwise, and the year 2010 is left as a reference. We run the regression by controlling for a full set of variables in Eq. (1) and province-by-year fixed effects ($\delta_p \times \mu_t$).

Fig. 3 displays the estimated coefficients and the 95% confidence intervals of β_m in Eq. (2). The small and insignificant coefficient on $RCI_c \times Year_t^{2012}$ suggests that there were no significant differences in the pre-trends for the counties with high and low levels of corruption. As expected, the counties more exposed to the campaign due to higher prior corruption began to exhibit lower poverty incidence in 2014, just two years after the anti-corruption campaign started. The magnitude of the estimated impacts is 0.028 for 2014 and 0.024 for 2018, slightly larger than that in column (3) of Panel B in Table 1. It's noteworthy that the effect persists even up to 2018, despite a decline in 2016. We interpret this as evidence that China's anti-corruption campaign has persistent effects in reducing poverty.[37]

As a further check for whether our results are biased due to the omitted variable, we conduct a placebo test by randomly assigning *RCI* to counties (see, for example, La Ferrara et al. (2012)). Specifically, by generating a random corruption severity ($RCI_{placebo}$) that differs from the actual corruption severity (*RCI*) for each county in 2012,[38] we construct a placebo policy variable ($RCI_{placebo} \times Post$) based on the random corruption severity. We then estimate Eq. (1) using the false policy variable

[37] From the insight of Balboni et al. (2022), assessing the long-run effect is crucial to drawing welfare conclusions for the poor.

[38] Since *RCI* is a standardized continuous variable, we draw randomly from a standard normal distribution with a mean of zero and a standard deviation of one.

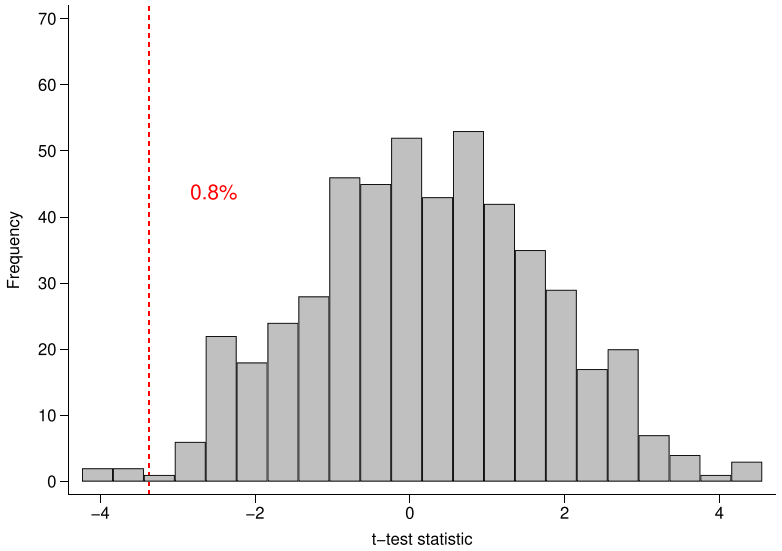

Fig. 4. A placebo test *Notes*: The X-axis presents the t-values of $RCI_{placebo} \times Post$ from the 500 randomized assignment exercises, and the vertical axis indicates the associated frequency. The red line is the true t-value from our baseline regression (column (3) of panel B in Table 1). The number in red indicates the percentage of trials that achieved a t-value smaller than the baseline finding. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and repeat the exercise 500 times. The distribution of the simulated t-values is shown in Fig. 4. As expected, the simulated t-values are centered around zero and the t-value of our true estimate (column (3) of panel B in Table 1) lies at the very end of the distribution.[39] This exercise suggests that our main results are unlikely to be biased due to omitted variables.

4.4. Additional robustness checks

In this section, we perform various robustness checks for our main findings.

Model specifications. We present alternative specifications of our main empirical strategy with the $3.2 poverty line in the first three columns of Table 2. Column (1) shows that our baseline estimate is robust to the inclusion of province-year fixed effects, which, by absorbing all of the provincial-level variations in both the time-series and cross-sectional dimensions, flexibly control for confounding factors, such as differential time trends, business cycles, and policies across provinces. In column (2), we interact all household- and individual-level control variables with *Post*, to allow the effects of the control variables on poverty incidence to differ between the pre- and post-campaign periods. In column (3), instead of interacting the initial level of economic development and population with *Post*, we interact each of the two county-level control variables with a second-order polynomial function of time trends, to more flexibly model the effects of the potential county-level confounding factors. In all three cases, the estimates remain both quantitatively and qualitatively very similar to our baseline estimate (column (3) of panel B in Table 1).

Sample selection criteria. Column (4) shows that our results remain robust if we use a balanced panel in which only families that were observed throughout the whole sample period are included. This is to ensure that our results are not driven by respondents' entry into or exit from the sample. Column (5) uses the full sample including the pre-campaign poor and non-poor groups. In column (6), we use only the first three waves of CFPS data, that is, the 2010, 2012, and 2014 waves. Since the large-scale "war on poverty" policy was put in place in 2015, we intend to eliminate its confounding effects in this exercise. The estimated effect remains robust with a balanced panel and data excluding the last two waves. In column (7), we use a sample including the migrating families and find the effect remains almost identical to that of the baseline.

Measures of (anti-) corruption. As described in Section 3.2, we use three variables, namely *Fee*, *Severity*, and *Performance*, to construct the regional corruption index (*RCI*). Here, we propose two alternative constructions of the corruption severity, as well as a treatment variable that exploits the provincial variation of the anti-corruption investigations.

First, we add a new variable *Trust* in the construction of *RCI*,[40] to capture the level of trust in local government officials, and derive a new variable of corruption severity RCI_1. Column (8) shows that both the coefficient and significance of the new key explanatory variables $RCI_1 \times Post$ have barely changed, compared to the baseline result (column (3) of panel B in Table 1).

[39] Only 0.8% (4/500) of the simulated t-values are negative and larger in magnitude than our t-value under the true policy. Our effect is thus significant at the 1% level even with this alternative inference procedure.

[40] The CFPS survey asks respondents to report the level of trust in local government officials, with answers ranging from 0 (very trustworthy) to 10 (very untrustworthy).

Table 2
Robustness Checks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Province-year FE	Controls × Post	Squared trends	Balanced panel	Whole sample	Exclude 2016&18	Include migration	Alt. RCI	Binary RCI	Anti-corr intensity
RCI × Post	-0.015**	-0.015***	-0.017***	-0.024***	-0.012***	-0.022***	-0.018***			
	(0.006)	(0.005)	(0.005)	(0.007)	(0.004)	(0.006)	(0.005)			
RCI_1 × Post								-0.016***		
								(0.005)		
RCI_2 × Post									-0.034***	
									(0.010)	
RCI × log(Convicted+1)										-0.011***
										(0.003)
Target	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	No	No	No	No	No	No	No	No	No
Adj R^2	0.24	0.23	0.23	0.26	0.29	0.21	0.23	0.24	0.24	0.24
Observations	32689	32689	32689	18430	46495	21525	34074	32689	32689	32689

Notes: The dependent variable is an indicator for a family with household income per capita less than $3.2 per day. Column (1) includes the province-year fixed effect. Column (2) adds interactions of household and individual level control variables with *Post*. Column (3) interacts each of two county-level control variables with a second-order polynomial function of time trends. Column (4) uses families that we observe throughout the five periods. Column (5) uses the whole sample including the pre-campaign poor and non-poor groups. Column (6) only uses the 2010, 2012, and 2014 waves of the CFPS data. Column (7) includes migration. Column (8) adds a new variable *Trust* to construct RCI_1. In column (9), we construct a dummy RCI_2 that takes the value 1 for a county with *RCI* larger than the median and 0 otherwise. In column (10), the post-campaign dummy is replaced with the intensity of the anti-corruption campaign in a province in year t, which is equal to the natural logarithm of one plus the cumulative number of high-ranking officials investigated for corruption in a province from 2013 up to year t for t equal to or larger than 2013. We set the intensity of the anti-corruption campaign equal to zero prior to 2013. All regressions include control variables of the baseline model in Eq. (1), household fixed effects, and year fixed effects. Standard errors clustered at the household level are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table 3
Government expropriation.

	Log (business income)			Entrepreneurship		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Rural	Urban	All	Rural	Urban
RCI × Post	0.120***	0.068*	0.184***	0.001	0.002	-0.002
	(0.031)	(0.040)	(0.046)	(0.002)	(0.002)	(0.004)
Target	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.50	0.37	0.57	0.01	0.01	-0.00
Observations	32089	20725	11059	32689	21166	11218

Notes: Columns (1)–(3) use the (log) household business income per capita as the dependent variable and columns (4)–(6) a dummy variable indicating whether a family runs a private business to proxy entrepreneurship. Columns (1) and (4) use the full pre-campaign poor family sample. Columns (2) and (5) use the rural families, whereas columns (3) and (6) the urban ones. All regressions include control variables of the baseline model in Eq. (1), household fixed effects and year fixed effects. Standard errors clustered at the household level are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Second, one may be concerned that our results are driven by some counties that report high levels of corruption. To check for this, we construct a variable RCI_2 that takes the value 1 if the county's *RCI* is above the median and 0 otherwise. This binary measure also further alleviates the measurement errors in the county-level *RCI*, though at the expense of losing some information. Once again, we find that our results are robust to this reclassification of the *RCI* measure (column (9)).

Finally, we also consider variations in the intensity of the crackdown on corruption across provinces. Instead of using the post-campaign dummy, we construct a provincial-level anti-corruption index using the number of convicted provincial- and sub-provincial-level officials, to capture the strength of anti-corruption efforts in a province over time. Specifically, following Giannetti et al. (2021), we set the intensity of the anti-corruption campaign in a province in year t equal to the natural logarithm of one plus the *cumulative* number of high-ranking officials investigated for corruption in a province from 2013 up to year t for t equal to or larger than 2013. We set the intensity of the anti-corruption campaign equal to zero before 2013. In column (10), we continue to find that households residing in counties more exposed to a corrupt environment benefit to a larger extent from the anti-corruption campaign.

5. Mechanisms

In this section, we explore four potential channels, namely reduced government expropriation, enlarged access to subsidies, enhanced formal financial support, and improved public goods provision, through which the anti-corruption campaign may reduce poverty incidence. To this end, we use the baseline model in Eq. (1) where we replace poverty incidence with the mediating variables. In order to take into account the possible differential effects between urban and rural households, as found in our baseline results (columns (4)–(5) of Table 1), we report separate results on the urban and rural subsamples alongside the result using the full sample.

5.1. Government expropriation

We first examine whether the relationship between the anti-corruption campaign and poverty alleviation is mediated by the effect of anti-corruption on government expropriation. In China where corruption is pervasive and protection for private property rights is weak, to meet various government regulations of business entry and ongoing operations, private businesses are subject to heavy expropriations from the government in the form of high informal levies, extralegal payments, and bribery (Du et al., 2015). We thus expect the campaign may contribute to constraining government expropriation of private properties, which in turn enhances business performance and promotes entrepreneurship.

We use business income per capita to measure business performance (the intensive margin) and a dummy variable indicating whether the household runs a private business as a proxy for entrepreneurship (the extensive margin).[41] In columns (1)–(3) of Table 3, we find that households in counties with higher corruption severity (*RCI*) in 2012 have experienced a significantly larger increase in (log) family business income after the anti-corruption campaign for the full pre-campaign poor household sample as well as the rural and urban subsamples. Based on the estimate of column (1) in Table 3, a one-standard-deviation increase in the corruption severity (*RCI*) implies about a 12.75 (i.e., $e^{0.12} - 1$) percent increase in the

[41] In CFPS 2010, the business income contains the family's net income from agriculture (farming, forestry, pasturing, sideline and fishery) as well as non-agriculture such as firms. In CFPS 2012–2018, we use the business income variable comparable to that in CFPS 2010.

Table 4
Subsidy availability.

	Log (subsidy)			Log (compensation for demolition)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Rural	Urban	All	Rural	Urban
RCI × Post	0.158***	0.121***	0.300***	0.010	0.473*	-0.197
	(0.034)	(0.038)	(0.078)	(0.182)	(0.241)	(0.281)
Target	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.35	0.32	0.43	-0.08	-0.09	-0.03
Observations	16377	12081	4081	2495	1173	1281

Notes: Columns (1)–(3) use the (log) household subsidy income as the dependent variable and columns (4)–(6) the (log) household compensation for housing demolition. Columns (1) and (4) use the full pre-campaign poor family sample. Columns (2) and (5) use the rural families, whereas columns (3) and (6) the urban ones. All regressions include control variables of the baseline model in Eq. (1), household fixed effects and year fixed effects. Standard errors clustered at the household level are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

family business income per capita after the campaign. In line with previous studies that have found China's anti-corruption campaign has improved firm performance (e.g., Giannetti et al. (2021)), this paper confirms the same findings by using comprehensive household survey data.

However, from the perspective of the extensive margin, there is only very weak evidence that suggests the anti-corruption campaign can encourage the start of a business among rural households (an estimate of 0.02 in column (5)). Given the uncertainty in the duration and strength of the campaign, combined with the fact that entrepreneurship requires initial sunk entry costs as well as per-period fixed costs, it's not difficult to understand the smaller effects on the extensive margin. While the anti-corruption campaign may have improved the business environment by reducing government expropriation on businesses mainly in the form of bribery, the amount of bribes may be small relative to the large entry and fixed costs. In an environment with high political uncertainty, a rational forward-looking individual thus may not be sufficiently incentivized to start a business under the current anti-corruption campaign. Overall, the results suggest that reduced government expropriation is likely to be an important underlying channel.

5.2. Subsidy availability

Massive corruption and elite capture are common in the practice of welfare projects, as detected in the literature (Reinikka and Svensson, 2004; Olken, 2006; He and Wang, 2017; Alatas et al., 2019). Since the anti-corruption movement would directly deter officials from stealing public funds, we conjecture that the anti-corruption campaign may improve the availability of transfers and subsidies to residents.

The CFPS survey provides detailed information on government subsidies received by households.[42] We use the (log) total amount of subsidy received by the family as the dependent variable in Table 4, and find a significantly positive association between *RCI* × *Post* and the amount of subsidy for all the three samples (columns (1)–(3)). The effect is also economically very large. For instance, our estimate suggests a one-standard-deviation increase in the pre-campaign corruption severity (*RCI*) translates into a 17% increase in the amount of subsidies received by a pre-campaign poor household post-campaign.

We then proceed to examine the effects on the amount of housing demolition compensation.[43] Our special interest in the housing demolition compensation lies in the very fact that governments in developing countries are particularly enthusiastic about requisitioning a large amount of land for urban construction and industrialization. The displaced residents typically receive a considerable amount of compensation payment for demolition and relocation from the government. However, the ambiguous compensation standard often breeds corruption and this large fortune thus readily becomes the target of corrupt local officials.[44] In the empirical analyses of this part, we restrict our sample to families that experienced a demolition at least once during our sample period. As shown in column (5), we indeed find evidence that the anti-corruption campaign has increased the amount of compensation received by the rural households. The effect is large in magnitude (a 60.5% increase) albeit only marginally significant, probably due to the relatively small sample size.

[42] Government subsidies include minimum living allowance (*Dibao*), reforestation subsidy, agricultural subsidy (including direct grain subsidies and farming machinery subsidies), *Wubaohu* subsidy (targeted at low-income, blind, disabled, elderly, and youth who cannot support themselves), *Tekunhu* subsidy (targeted at very poor families), work injury subsidies to lineal relatives, emergency or disaster relief (including material goods), and other subsidies from the government.

[43] The compensation mainly comes in the form of money or housing. If the compensation is a new house, the market value of the house is provided in the CFPS.

[44] See https://www.sohu.com/a/277987844_99896035 for a related news report.

Table 5
Formal financial support.

	Formal credit availability			Formal credit rate		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Rural	Urban	All	Rural	Urban
RCI × Post	0.013***	0.010***	0.012***	0.025***	0.030***	-0.003
	(0.003)	(0.004)	(0.004)	(0.010)	(0.011)	(0.020)
Target	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.24	0.25	0.20	0.37	0.39	0.32
Observations	32633	21128	11199	5859	4270	1440

Notes: Columns (1)–(3) use a dummy variable indicating whether a family has any bank loans as the dependent variable and columns (4)–(6) the proportion of bank loans in all loans. Columns (1) and (4) use the full pre-campaign poor family sample. Columns (2) and (5) use the rural families, whereas columns (3) and (6) the urban ones. All regressions include control variables of the baseline model in Eq. (1), household fixed effects and year fixed effects. Standard errors clustered at the household level are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

5.3. Formal financial support

Plentiful cross-country evidence suggests that financial inclusion helps to promote economic growth and to reduce inequality and poverty (Beck et al., 2000; Park and Mercado, 2018; Omar and Inaba, 2020). Notably, empirical studies using subnational and survey data find access to banking services is critical for the poor to escape the poverty trap through the credit channel, especially for the borrowers who already had a business (Banerjee et al., 2015; 2019; Meager, 2019). In this paper, however, we focus on an institutional barrier that hinders effective access to formal financing—corruption.[45] Corruption in credit lending reduces the efficiency in capital allocation and diverts capital from more productive to less productive activities (see, for example, Khwaja and Mian (2005)).

Like most developing countries, there exist many credit products designed for the poor in China, especially after the "war on poverty" program. Credit funds for poverty alleviation can be roughly classified into two categories: the "Microcredit Loans (*fupin xiao'e daikuan*)" for the impoverished households and the "Poverty Alleviation Loans with Discounted Interests (*fupin tiexi daikuan*)" mainly for the local firms and infrastructure construction. However, the poverty alleviation loans in China, unlike microfinance in other developing countries, are mostly operated by state-owned financial institutions. This implies that political factors play a much bigger role in the allocation of credit resources than credit markets.[46] Given that China's banking sectors dominated by state-owned banks were corrupt and also heavily targeted by the anti-corruption campaign, we expect the campaign may have a bearing on the process of credit allocation in the banking sector.

We first check the impacts of anti-corruption on the extensive margin of formal financing, defined as whether a family has any outstanding bank loans (excluding housing loans).[47] The results are presented in columns (1)–(3) of Table 5, which show that stronger exposure to the anti-corruption campaign is associated with a significantly higher probability of obtaining bank loans after the campaign for both types of households. We then turn to the effects on the intensive margin of formal financing. For households with any outstanding loans,[48] we calculate the proportion of outstanding *bank* loans as the dependent variable in columns (4)–(6) in Table 5. We find a positive, large and significant effect for the whole sample as well as the poor rural subsample. Our interpretation of these results is that thanks to the large-scale crackdown on corruption, formal bank financing has not only become more accessible to households, but also accounted for a larger proportion of their borrowing portfolios. We argue this is because the campaign may have made the credit allocation process fairer and more transparent, leaving less room for corruption in the process. Our findings are also consistent with Li et al. (2021), which find the recent anti-corruption investigations in China have resulted in credit reallocation from less productive SOEs

[45] A related report shows how corruption hinders access to poverty alleviation microloans in China and the effect of the anti-corruption campaign. Details come from https://news.cgtn.com/news/2020-08-09/In-data-China-s-fight-against-corruption-in-poverty-alleviation-SO8OgC70Q0/index.html.

[46] More policy details can be found in an official report—Zhao et al. (2016).

[47] Bank loans here include both commercial loans and preferential policy loans, so our results should be interpreted with caution. While we admit that the ideal outcome variable is access to poverty alleviation loans for the poor group, the CFPS dataset doesn't provide such detailed loan information. Since our sample only consists of the (potential) poor families, most of which cannot have access to commercial loans, we believe our results can still shed light on financial inclusion.

[48] Loans include both formal loans (i.e., bank loans) and informal loans that include borrowings from relatives, friends or other individuals and institutions (e.g., private lending institutions).

Table 6
Public goods provision.

	Tap water			Electricity		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Rural	Urban	All	Rural	Urban
RCI × Post	-0.005	-0.003	-0.012*	-0.000	0.011	-0.025**
	(0.004)	(0.005)	(0.007)	(0.007)	(0.008)	(0.013)
Target	0.191***	0.123***	0.320***			
	(0.033)	(0.043)	(0.061)			
Target	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.57	0.53	0.60	0.21	0.22	0.20
Observations	31588	20463	10809	20441	13204	6856

Notes: Columns (1)–(3) use a dummy variable indicating whether a family uses tap water for cooking as the dependent variable and columns (4)–(6) a dummy variable indicating whether a family has constant access to electricity. Columns (1) and (4) use the full pre-campaign poor family sample. Columns (2) and (5) use the rural families, whereas columns (3) and (6) the urban ones. All regressions include control variables of the baseline model in Eq. (1), household fixed effects and year fixed effects. Standard errors clustered at the household level are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

to more productive non-SOEs. Both the findings of Li et al. (2021) and ours suggest that the credit allocation has become more efficient since the campaign, at least in a way less dependent on bribes and political connections.[49]

5.4. Public goods provision

Corruption in public projects is the main focus of many early studies (Reinikka and Svensson, 2004; Olken, 2006; 2007; 2009). If corruption is indeed the main obstacle to the public provision of high-quality infrastructure, the anti-corruption campaign is conjectured to reverse the situation. However, as discussed at length in Section 2.2, the reduced rent-seeking opportunities as well as the "chilling effect" induced by the anti-corruption campaign may imply the opposite, particularly for infrastructures. Given the data availability, here we consider two basic infrastructures that matter for daily life: the use of tap water for cooking and constant access to electricity (i.e., almost without outrage), both of which are also important dimensions in the multidimensional poverty assessment (Alkire et al., 2021). The results across columns (1)–(6) in Table 6 show a negative correlation between *RCI* × *Post* and *Tap water* or *Electricity*. Particularly, the effect of the campaign on the use of tap water and constant access to electricity turns out to be negative and statistically significant for urban poor residents. This verifies our second set of arguments in Hypothesis 2, that the anti-corruption campaign may indeed lead the local officials to shirk their duties in the provision of infrastructure projects. This indicates the side effects of the anti-corruption campaign on public goods provision outweigh the positive effects in the context of China. This finding complements studies on the adverse consequences of the anti-corruption campaign such as bureaucratic slack (Morduch, 1994; Wang, 2021). By contrast, we find China's "war on poverty" program captured by the *Target* variable has significantly increased the use of tap water,[50] indicating the large-scale targeted transfer programs can more effectively improve the basic living facilities.[51]

[49] It should be noted that the positive effect of anti-corruption on the formal financial support we found in this section could work through both the demand and supply sides. From the demand side, the finding in Table 3 that constrained government expropriation after the campaign improved business performance and encouraged entrepreneurship indicates a greater demand for bank loans to expand or start their business. From the supply side, the campaign may increase the credit availability to households and their businesses due to the more transparent and efficient allocation of credit. In the online Appendix Table A.3, we try to separate the two effects by adding the entrepreneurship indicator as an additional control in Table 5. Besides, we also include (log) household income per capita as an additional control to exclude the possibility that anti-corruption enhances loan access (amount) mainly through better loan eligibility due to increased income. We find the effect remains almost unchanged after controlling for the demand for loans and income. Thus we conclude the effect on the supply side dominates.

[50] Alternative options include water from rivers, lakes, springs, wells, ponds, and cellars. Since data on constant access to electricity are only available up to 2014, *Target* cannot be controlled in columns (4)–(6).

[51] It should be noted that in this part we aim to examine the effect of anti-corruption on the provision of public goods. However, due to data limitations, we only have information on individual use or access to these facilities. To isolate the income effect that may confound our result, we also control for household income per capita. The results remain very similar without income as a control.

Table 7
Political connections.

	Log (household income per capita)			
	(1)	(2)	(3)	(4)
	CPC household	Non-CPC household	Cadre household	Non-cadre household
RCI × Post	-0.009	0.043***	-0.281*	0.036**
	(0.037)	(0.013)	(0.168)	(0.018)
Target	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj R^2	0.32	0.29	0.18	0.33
Observations	3057	27537	364	21442

Notes: The dependent variable in the table is the (log) household income per capita. Regressions in this table are based on the pre-campaign poor household sample. Column (1) uses the subsample of CPC families (defined as families where at least one family member has the CPC membership). Column (3) uses the subsample of cadre families (defined as families in which at least one family member has worked in the government or public sector). All regressions include control variables of the baseline model in Eq. (1), household fixed effects and year fixed effects. Standard errors clustered at the household level are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

6. Additional analyses

6.1. Political connections

In this section, we investigate the heterogeneous effects of the campaign across households with different characteristics. A relevant characteristic in our context is political connectedness. In the context of China, it is almost impossible for the poor to obtain CPC membership, just as the party constitution states that the CPC always represents the advanced "productive forces". Likewise, state sector employment, often considered as an "Iron Rice Bowl", is attractive to most people (Bai et al., 2021), albeit mostly unavailable to the poor.[52] If the income-enhancing effect we find only exists among those politically connected families, it may reflect a redistribution of interests within the ruling class. On the contrary, if evidence shows that anti-corruption efforts are more beneficial to the non-politically connected families, we believe this campaign indeed increases income for people at the bottom of the income distribution.

We measure a family's political connection in two ways: the CPC membership and cadre experience.[53] We run regressions separately on the households with and without connections. Columns (2) and (4) in Table 7 show that the income-enhancing effect of China's anti-corruption we found before is mainly driven by the non-connected families. Due to the inaccessibility of party membership or state sector employment among the poor, this finding can be regarded as supplementary evidence that the campaign indeed benefited individuals at the bottom of the income distribution and further helped them get rid of poverty. By contrast, our results for the politically connected families reveal negative effects of the campaign on their incomes, albeit only marginally significant in column (3).[54] The clear contrasts between the two sets of results lend some support to the effect we found before being accrued mainly to the most underprivileged, thus capturing the poverty-reduction effect. Overall, anti-corruption efforts contribute to narrowing the income gap between the two groups by significantly increasing the incomes of the non-connected. Our findings are consistent with the firm-level evidence that firms without political connections benefit more from the anti-corruption campaign (Xu and Yano, 2017; Giannetti et al., 2021; Li et al., 2021). Different from these studies, our study provides more intuitive evidence on the welfare consequences rather than focusing on firm performance.

6.2. Distributional effects

We now extend our previous analyses to examine whether there are distributional impacts such that households at different quantiles of income are differentially affected by the anti-corruption campaign. Particularly, we are interested to

[52] These two points can be seen in the relatively few observations in columns (1) and (3) of Table 7.

[53] Specifically, if there is at least one family member with CPC membership within the household, it is defined as a CPC family. Likewise, we define the cadre family as one in which at least one family member works in the government or in a public organization affiliated with the government ("*shiye danwei*" in Chinese).

[54] The negative estimation results coincide with some facts about China's anti-corruption campaign. First, as an important action against corruption, the Politburo of the CPC Central Committee issued the "Eight-point Regulation" policy to cut the excessive and unreasonable welfare of employees in the state sector in 2012. Second, the strong deterrent effects generated by the anti-corruption campaign forced the politically connected group to refrain from corruption and other illegal conduct. As a result, the economic benefits of political privileges declined. In the CFPS dataset, since the non-monetary remuneration is also included in the individual income variable, our results can reflect these income changes. However, as correctly pointed out by one referee, caution should be used in interpreting the results since the sample size is small for the connected families.

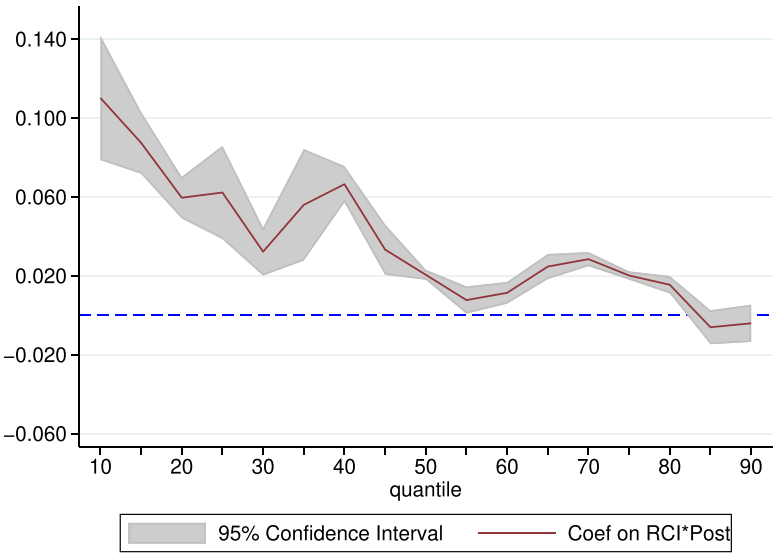

Fig. 5. Panel quantile regression analysis. *Notes*: This figure shows results from panel quantile regressions estimation of Eq. (1) with the (log) household income per capita as the dependent variable at every 5 percentiles from the 10th to 90th quantile of the income distribution. The estimated coefficients and 95 percent confidence intervals (CIs) of $RCI \times Post$ are presented. The CIs are calculated pointwise from the posterior distribution of MCMC draws.

know whether all the residents, within the pre-campaign poor sample, benefited equally from the campaign or some subgroups disproportionately benefited more. Using the recent panel quantile regression technique (Powell, 2022),[55] we estimate Eq. (1) with the logarithm of household income per capita as the dependent variable. We plot the estimate across the distribution of the dependent variable in Fig. 5. Consistent with our expectations and previous findings, Fig. 5 shows that as the level of household income increases, the income-enhancing effect of the anti-corruption campaign gradually dwindles. Specifically, the effect turns out to be very large and significant below the 40th percentile of the income distribution and becomes close to 0 beyond the 85th percentile. This evidence once again supports that China's anti-corruption campaign is disproportionately more beneficial for the low-income group. In addition, this highlights that the anti-corruption campaign could level the playing field by reducing inequality in the earnings distribution for those more exposed to the campaign.

7. Concluding remarks

In this paper we exploit the negative shock of corruption in China, to investigate the consequences of radical, externally imposed institutional changes on subsequent poverty incidence. Using datasets from five waves of CFPS, we find robust evidence suggesting that China's anti-corruption campaign increases the income and decreases the poverty incidence of the (potential) poor group. Our work also explores three plausible mechanisms through which the campaign affects poverty incidence: reduced government expropriation, enlarged access to subsidies, and enhanced formal financial support. However, we find null or even negative effects on the provision of infrastructures, probably due to local officials' reduced expected net benefits from rent-seeking in the public projects and the "chilling effect" after the campaign. Additional analyses provide evidence that families with low income and without political connections disproportionately benefited more from the campaign. These findings are important not only because they provide a timely and systematic appraisal of the socioeconomic impact of China's anti-corruption campaign, but also because of their implications on the crucial role of institutions in poverty alleviation. Most recent studies have adapted the technocratic approach to study poverty alleviation programs, based on the belief that radical changes in institutions or government performance improvement are hard to take place in a short time. This paper attempts to fill this gap in the literature by exploiting a plausibly exogenous shock induced by China's recent large-scale anti-corruption campaign.

This article has two explicit policy implications. First, our findings directly speak to the crucial role of institutions in shaping poverty. While the large-scale investment and direct subsidies led by the governments have played an important part in poverty alleviation, the findings presented here suggest that the role of institutions should not be ignored and cannot be overemphasized. Without a sound institution in place to check corruption, on the one hand, the theft of government resources would render otherwise worthwhile government projects non-cost-effective; on the other hand, business activities are hampered by excessive government expropriation that imposes an additional tax. While it seems difficult for China to undergo a significant institutional improvement in a short time, the anti-corruption campaign turns out to be an effec-

[55] The quantile estimator for panel data recently developed by Powell (2022) can adequately control for the non-additive households fixed effects. This estimator is consistent for small T and straightforward to implement. See Powell (2022) for more details.

tive policy initiative in this regard. Second, our analysis points to one of the side effects of anti-corruption—bureaucratic slack, embodied in the public good provision. One explanation is since the process of infrastructure provision features heavy state-business interactions, which may easily invite visits by anti-corruption inspectors, bureaucrats in charge strategically reduce their overall amount of work activities in the shadow of the anti-corruption campaign, thus resulting in the under-provision of public goods (Wang, 2021). Besides, the reduced rent-seeking opportunities in the infrastructure projects after the campaign may also account for this negative effect. The unintended negative consequence should be borne in mind by all countries preparing to fight corruption. Inspired by China's experience, we suggest one potential solution is to strengthen monitoring from upper-level governments. Specifically, performance in the public good provision can be incorporated as an important criterion in the overall evaluation of local officials. Moreover, upper-level governments can also directly dispatch cadres to poor villages to take over the poverty alleviation work.[56]

Naturally, some findings presented from China can be extrapolated to other economies, but with caution. First, the impact of anti-corruption on poverty reduction may be significant only when the government is also an important player in promoting poverty alleviation, as shown in the case of China. Second, the mechanism of enhanced formal financial support we find may not hold in countries where governments do not have strong control over banks. Most of the credit resources for poverty alleviation loans in China are allocated by state-owned banks, in contrast to the prevalent cases in many developing countries where commercial microfinance institutions dominate in lending to the poor. Nevertheless, it is noteworthy that our findings do suggest that the radical anti-corruption campaign can have beneficial consequences for the poor, at least in the context of China in the short to medium term. While the large-scale anti-corruption campaign is less common worldwide, it is by no means unique to China. Many developing countries, such as Vietnam (Sharma et al., 2021) and Brazil (Avis et al., 2018), have also taken serious actions to combat corruption in recent years. Future research and evidence from other developing countries in terms of the individual welfare consequences of anti-corruption efforts are highly expected, which helps check the generalizability of our key findings.

Data Availability

Anti-corruption and Poverty Alleviation: Evidence from China (Mendeley Data)

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Complementary Figures and Tables

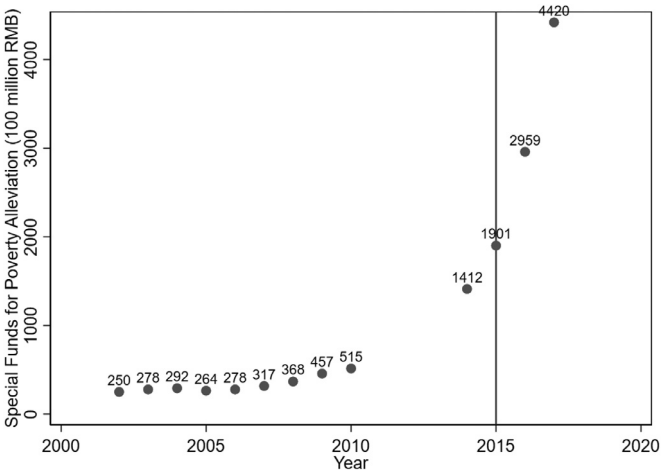

Fig. A1. Total investment of special funds for poverty alleviation in poverty-stricken counties. *Notes*: Special funds for poverty alleviation include: poverty alleviation discount loan from central government, special poverty alleviation fund from the central government, special project subsidies for returning farmland to forests and grasslands from central government, subsistence allowance funds from central government, poverty alleviation funds from provincial finance, international poverty alleviation funds, and other funds. All data come from the *Poverty Monitoring Report of Rural China*, and data from 2011 to 2013 are missing.

[56] Although these two ways of enhancing monitoring are common in China, they are more applicable to non-democracies, especially the latter one requiring upper-level governments to have strong personnel controls.

Table A1
The pre-campaign poor household under different poverty lines.

Standard	Deviation obs.	Deviation rate	Observations	Households
\$3.2/day	3502	7.5%	21126	5194
1.5 × \$3.2/day	2390	5.1%	27766	6853
2 × \$3.2/day	1828	3.9%	32689	8092
2.5 × \$3.2/day	1455	3.1%	36047	8955

Notes: The second column reports the number of observations that are not defined as the pre-campaign poor household but fall into poverty under \$3.2/day criteria in the post-campaign period. The deviation rate in the third column is the number of deviation observations divided by the full sample size (46,495). The fourth column shows the number of observations in the baseline regression, and the last column provides the corresponding number of pre-campaign poor households.

Table A2
Poverty lines in RMB.

Standard	2010	2012	2014	2016	2018
\$3.2/day	4097.50	4433.13	4647.29	4807.30	4984.40
\$5.5/day	7042.58	7619.44	7987.53	8262.54	8566.93
40% relative poverty	5159.30	6021.93	6407.16	6900.28	7590.26

Notes: We use the 2011 PPP conversion factor to convert USD to RMB. To be clear, the \$3.2/day and \$5.5/day poverty lines presented here are in current prices, but we use these two poverty lines at constant 2010 prices in the empirical analyses. The relative poverty lines are 40% of the biennial provincial average household disposable income per capita and are deflated to 2010 RMB by provincial CPI. The PPP conversion factor data are from the World Development Indicators database.

Table A3
Polychoric PCA result for Regional Corruption Index (*RCI*).

Component	Eigenvalue	Proportion	Variable	Comp1	Comp2
Comp1	1.533	0.511	*Fee*	0.514	0.776
Comp2	0.851	0.283	*Performance*	0.646	-0.071
Comp3	0.616	0.205	*Severity*	0.564	-0.626

Notes: The last columns report the factor loading of each variable for the 1st and 2nd components.

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