Leaving No One Behind: China's Central-Local Governments and Corporate Tripartite Collaboration to Reduce Poverty

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First draft: Aug 2023
Latest draft: Dec 2024

Acknowledgement: This research project is not funded by any government agents or for-profit organizations. We do not see any conflict of interest.

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Abstract:

We examine China's Targeted Poverty Alleviation Program in a hierarchical central-local-corporation tripartite collaboration framework. It started in 2014 but made only slow progress initially. To help accelerate the program, the central government permitted full tax deductions for corporate anti-poverty spending starting 2019. The progress accelerated. On average, central-government-owned SOEs donated more than local-government-owned SOEs, and private companies donated the least (but donated the most in the aggregate). Corporate spending was higher in locations with greater tax revenue and when the central government could better monitor firms' support. Furthermore, firm-level efforts significantly reduced poverty, while most government public spending did not.

JEL Classification: I38, H71

Keywords: central-local-governments and corporate collaboration, political economy of poverty alleviation, corporate anti-poverty spending, tax deductions

I. INTRODUCTION

This paper uses micro-level data from 2016 to 2020 to examine the under-explored and yet successful collaboration between China's government and corporate sector to reduce poverty, focusing on the mechanisms behind its outcomes.

China's rapid growth since 2000 drew global attention; its per capita GDP rose at about 17% (CAGR) from a nominal US$951 in 2000 to a nominal US$6,383 in 2012, when the Hu-Wen regime ended. However, the economic gains were disturbingly uneven: the Gini coefficient grew from 0.412 in 2000 to 0.474 in 2012, which was high by most standards. In 2012, the National Bureau of Statistics of China's records showed that the poverty population was at 7%, or at an absolute level of 98.99 million people out of a population of 1.4 billion. Moreover, the number of counties designated as "impoverished" was 29% (843 out of a possible 2852). Reducing poverty is of significant importance for China, given its rapid growth both in the economy and in economic disparities, yet comprehensive investigations remain scant.

This paper fills this gap by studying China's recent ***Targeted Poverty Alleviation (TPA)*** program. In 2012, when President Xi assumed office, China made 'reducing poverty' a central policy priority.[1] In 2014, the central government formally launched its TPA program, the single most important national poverty reduction program ever (Li et al., 2023). At the end of 2015, the central government explicitly set a national goal to eliminate poverty by 2020, a short five-year timeframe.[2] The progress against poverty appeared to be impressive, as Figure IA suggests. However, the progress was uneven over time and across regions. The drop in the number of

[1] In 2012, the Communist Party of China (CPC) Central Committee pledged to reduce poverty as a central priority. Refer to http://www.xinhuanet.com/politics/leaders/2021-02/25/c_1127140240.htm. In Chinese. Last accessed on July 12, 2024.

[2] On Nov 29, 2015, CPC Central Committee and the State Council issued a document "Decision on Winning the Tough Battle Against Poverty" to clearly set the goal to eliminate poverty by 2020.

counties in poverty was slow from 2012 to 2016 (see Figure IB). Similarly, provincial-level progress in reducing the poverty population was slow before 2018, as indicated by the median provincial poverty reduction rate (see Figure IC). More was needed to meet the target of eliminating poverty by 2020 and the central government thus called on the corporate sector to help accelerate progress – it provided full tax deductions for corporate donations to targeted poverty-stricken areas for poverty alleviation purposes from Jan 1, 2019, onward for six years. Figures 1 B and C show that poverty reduction picked up its pace in 2018, with the most dramatic corresponding progress in 2019.

TPA program reduced the official poverty population to zero, and government statistics claimed that no counties remained in poverty by 2020. Although some might reasonably question the data's integrity, the record of lifting 100 million above poverty in less than a decade is enviable and, some might say, unparalleled in human history (BBC, 2021; World Bank, 2022). The mechanisms of TPA to attain this phenomenal poverty reduction is worthy of investigation.

This study assesses the intricacies of the TPA program, by using micro-level data and regression analyses to uncover and validate two key institutional details of the TPA program: (i) the dual facilitating and gatekeeping roles played by local governments, and (ii) the incentivization provided to corporations. Our analyses also show that central-local government generic spending did not effectively reduce poverty, while targeted corporate spending did.

China, a central government-led country or an authoritarian state, could have an advantage in mobilizing resources to engineer social changes, but such efforts are not automatic and may not deliver the intended outcome (Ciancio & García-Jimeno, 2024). Indeed, the TPA program initially generated results only gradually. The central government mobilized local

governments in 2014 to collate precisive information on impoverished individuals and their causes; the records were called the "***Poverty Registry***." The central government then made transfers to local governments to support poverty reduction spending. As the desired results were not being seen fast enough, starting in 2019, the central government provided full tax deductions to incentivize corporations to spend on actions that alleviate poverty in the Poverty Registry. The local governments then played two roles. First, they provided poverty registry information to corporations. Second, they were close-range gatekeepers that ascertained whether corporate spending indeed reduced poverty. This is because, by the nature of the central-local government tax-sharing scheme, permitting tax deductions would reduce local governments' fiscal revenue. In summary, the TPA is a central-local-corporate tripartite collaboration, which was made more nuanced over time, that had achieved an impressive poverty reduction record.

Our study is motivated by a paradox in the TPA program: how the same public and private partnership in China that generated fast growth and inequality in earlier years was leveraged in later years to reduce poverty. Qian and Xu (1993, pp. 541-548) suggest that China's governance system approximates an "M-form hierarchical system." Chandler (1969) identified how U.S. large enterprises used an M-form structure to create a decentralized multi-division organization with semi-autonomous sub-divisions. Analogously, Qian and Xu (1993:542) write that China's central authorities governed the country "using a multi-layer-multi-regional hierarchical format based on a geographic principle which emerged since 1958."

To answer this paradox, we examine the institutional design that directs the tripartite collaboration: In the earlier years after the 1978 reforms, the governments at the lower levels

of the hierarchy had little bargaining power *vis-a-vis* their superiors; however, they had autonomy in developing their regions by establishing market-oriented enterprises and engaging in other activities outside the direct purview of the central government. As the reforms progressed into the 1990s, when the market took a more significant role in directing resource allocation, there was rigorous competition among local government officials, where their region's comparative economic performance significantly advanced their careers. Zhou (2007) states eloquently that local bureaucrats engaged in an economic growth tournament for career advancement across China. Morck and Yeung (2014; 2018) expand on this framework. They identified that the multi-layer, multi-regional hierarchy included governments using state-controlled banks and enterprises to achieve their agenda for economic growth. Deng et al. (2015) showcase how implementing this framework, alongside a massive increase in money supply, enabled China to avoid the economic setbacks that befuddled many nations during the 2008 Great Financial Recession.

These papers suggest China's fast growth results from its hierarchical central-local-corporate tripartite collaboration framework combined with its focus on the unified objective of economic growth. However, the framework could also allow economic disparity to increase when equality was not a government objective. The TPA program introduced poverty reduction as an additional objective. With the newly added policy objective, the same hierarchical central-local-corporate tripartite collaboration effectively reduced poverty. The local governments were the facilitators and gatekeepers, and they enabled the corporate sector to play a key role. In the TPA, the central government praised corporate responses to calls to reduce poverty as described in the White Book of Poverty Alleviation: China’s Experience and Contribution

(State Council Information Office of the People's Republic of China, 2021): "In their poverty alleviation action, private enterprises have offered targeted assistance to registered poor villages and households by developing industries and businesses, creating jobs, carrying out public benefit programs, and helping them access education. From 2015 to the end of 2020, 127,000 private enterprises participated in this action and offered targeted help to 139,100 poor villages (including 73,200 registered ones), benefiting 18.04 million poor people."

We next shed light on the mechanisms of the TPA by examining the sequential steps and the incentives used by the tripartite collaboration to reduce poverty. We first examine how the corporate sector's response to the central government's call to action varies according to (i) firms' dominant stakeholders, (ii) local government affordability, and (iii) central government's control, monitoring, and information. To proceed, we differentiate three types of firms — central-controlled state-owned enterprises (CSOEs), local-controlled state-owned enterprises (LSOEs), and privately-owned enterprises (POEs). As with corporations in most economic contexts, each of the three types of firms must serve its dominant stakeholder's interests: the central government for CSOEs, the local government for LSOEs, and private shareholders for POEs. Thus, their level of response to the central call to action depends on the dominant stakeholder's objective function. We find that CSOEs are the most responsive to the added 2019 tax deductions for spending on the poverty reduction program because their dominant stakeholder, the central government, had poverty reduction as a policy priority. LSOEs become more responsive to the program when their local government had higher fiscal revenues to afford tax deductions. POEs would be the least responsive, because their dominant shareholders want to preserve resources and avoid political extractions. That said, POEs, in the aggregate,

made the lion's share of donations in all of our sample years (2016-2020) because there are many more listed POEs than listed SOEs.

Importantly, these three types of firms are in different regions in China and are subject to different levels of central and local government monitoring. We further find that the information available to the central government matters: firms with a greater analyst following or a physical presence in the capital city donate more in response to the TPA. We also find that while the central government gave honorific awards to corporate donors to the tax deductions program, the local governments did not.

These findings validate the underlying incentive mechanisms embedded in the TPA, which helps to create an effective central-local government-corporate tripartite collaboration. First, firms' responses to the central call to donate to reduce poverty depended on the central government's degree of control and information on the firms, as well as the firms' dominant shareholders' preferences. Second, the local governments obeyed but did not necessarily fully embrace the central anti-poverty agenda. Because they were both a facilitator and a gatekeeper of tax deductions, resultant donations were less when a local government had fewer fiscal resources to absorb the reduced income from tax deductions. Indeed, we find evidence that local governments are less enthusiastic about encouraging corporate donations than the central.

We find useful additional results, namely, that the tax deduction program had prompting and auditing effects. Across all three types of firms, those that issued corporate social responsibility (CSR) reports did not donate much to help people in poverty before the program; however, they all did so after the introduction of the 2019 tax deduction program. The program served an auditing function as local governments intensified enforcement when it impacts their

tax revenue. Even those CSOEs and LSOEs that did not issue CSR reports also donated to poverty reduction after the 2019 tax reductions program. Second, donations exhibit an interesting pattern. Some POEs reacted to the 2019 campaign by donating to redistribution programs, which various levels of the Chinese government did not emphasize. LSOEs contributed more to industry development and employment opportunities, which strategically helped local governments achieve a better economic performance within the short tenure of mayors and party secretaries.

Finally, we assess the effect of government and corporate spending on reducing poverty. We find that overall corporate donations and efforts, like economic growth, contribute notably to poverty reduction, while most local governments' related spending does not. Thus, the 2019 tax deduction program that intensified corporate donations and efforts duly accelerated the pace and scope of poverty reduction. These observations suggest the difference in the direct effectiveness of private spending versus government spending in reducing poverty. Corporate spending for poverty reduction, as stimulated by tax deduction allowance, is targeted and gives a durable lift because it motivates a corporation to do what a company does as a normal course of business, e.g., job training, immediate job creation, and immediate creation of sustainable economic opportunities. Furthermore, the economic impact of such expenditures on earnings guides spending. Government spending on reducing poverty is mainly a transfer, it is not necessarily result-oriented, and bureaucracy can hinder its effectiveness.

Our study is noteworthy for two reasons. Economists often focus on macro-level policies to overcome poverty, such as government-led redistributive programs (Squire, 1993) and multilateral development banks (Birdsall & Londono, 1997). Financial economists have

studied the impact of financial inclusion (e.g., Agarwal et al., 2017). Development economists have successfully used experimental methods to learn about the effectiveness of small-scale policy interventions to help the poorest. Indeed, Professors Banerjee, Duflo, and Kremers won the Economic Nobel Prize in 2019 for their contributions to such work (Banerjee & Duflo, 2011). Still, our understanding of corporate anti-poverty actions is nascent. This study provides a timely assessment of the TPA program in China by documenting the hierarchical central-local government-corporation tripartite collaboration to reduce poverty and exploring the underlying mechanics and economic logic behind its outcome. It illustrates that while the government alone had slow progress in attaining the social goal (poverty reduction), companies made unique and effective anti-poverty efforts that governments cannot easily substitute. Poverty reduction became most effective after the incentive-aligned tripartite collaboration entered.

We also extend our understanding of how to motivate CSR actions. Governments often use tax deductions or other fiscal incentives to induce preferred corporate behaviors (Chandra & Long, 2013; Chen et al., 2021). Our study suggests that tax deductions have a prompting and auditing effect to induce corporate reactions to a central government policy. Therefore, the policy decision hinges on more than trading off tax revenue for a targeted corporate sector's spending for a social objective; it also depends on how local agents shape their enforcement of policy according to their preferences and constraints.

The paper is organized as follows. In Sections II and III, we present the background of TPA and our empirical approach, respectively. In Section IV, we present our baseline results and robustness checks. Section V provides evidence to validate critical underlying assumptions: local governments prioritize poverty reduction less than the central government, and tax

deductions are an auditing device for corporate actions. Section VI reports additional empirical information on firms' anti-poverty approaches. In Section VII, we present the empirical results on the effect of government and corporate spending on anti-poverty actions. Discussions and conclusions follow in Section VIII.

II. BACKGROUND

A. Targeted Poverty Alleviation Program in China

The Central Government's Initiation of Targeted Poverty Alleviation Program

Even given its unprecedented economic growth since 2000, China's impoverished population stood at 98.98 million in 2012, according to the National Bureau of Statistics of China. In 2013, the Xi government declared that combating poverty was a high central policy priority. President Xi introduced the concept of targeted poverty alleviation. Later, in March 2014, Premier Li Ke Qiang formally launched the ***Targeted Poverty Alleviation (TPA)*** program (精准扶贫), which emphasized that poverty alleviation efforts must reach individuals and households genuinely in need and effectively deliver targeted outcomes (State Council Information Office of the People's Republic of China, 2021). Unlike past poverty reduction programs, the TPA program focused on individuals, alleviating targeted households instead of poverty counties (Zhang et al., 2023).

Poverty Registry and Local Governments

As a first step, the central government assigned local officials to identify impoverished individuals accurately. As part of this construction of the ***'poverty registration'*** information system, the local officials determined the causes of poverty and kept extensive and updated

records of these individuals. This database was an essential institutional innovation established to facilitate the TPA program. All TPA anti-poverty efforts had to target individuals and families that were "***registered impoverished households"*** as formally listed in the "***poverty registry.***"

The poverty registration process involved the following steps. A household initiated an application to register as being in poverty. Local grassroots officials then conducted home visits to screen the applicant's eligibility. The primary criterion was low income, with the national rural poverty line as a benchmark. Other criteria included housing conditions, education, health, and family members' occupations. A local official's scrutiny was necessary to adapt location-specific eligibility criteria and rule out households manipulating their conditions to receive TPA intervention. Finally, the local officials listed suggested pre-designated anti-poverty actions tailor-made for each household accepted into the poverty registry. The list of approved registered poverty households and recommended actions were subject to higher-up officials' approvals (Zhang et al., 2023).

Furthermore, these officials had to update the poverty data regularly and deregister individuals already lifted from poverty. An annual review of the information by third parties was conducted on the deregistration processes. (From here on, we define people in poverty as those on the poverty registry.)

This detailed poverty registration database became an information gateway that directed anti-poverty efforts for both the public and private sectors. Its localized information enables the formation of location-specific and condition-specific measures that can effectively help those in the registry.

Additional Initiative: Government-Corporate Partnerships to Reduce Poverty

Figure IA illustrates that the poverty population declined steadily after launching the TPA program. However, it is unclear how effective the TPA program was initially. One would expect a general decline in poverty as China's per capita GDP rose 30% from USD 7,636 in 2014 to USD 9,905 in 2018. Also, the central government allocated special funds to the local governments to reduce poverty.

That said, Figure IB shows that the number of "impoverished counties" included in the poverty registry has been stubbornly high before 2018. Furthermore, Figure IC shows the median poverty reduction rate across provinces after the TPA was launched. From 2014 to 2017 it increased slowly; it reached the 2012 level only in 2016 and the higher 2011 level only in 2017. These patterns suggest that the central government would have reasons to be dissatisfied with the TPA program's progress, thereby creating doubts that eliminating poverty by 2020 was a reachable target.

Consequently, in 2018, the central government intensified its emphasis on eliminating poverty and issued a document outlining the directional poverty reduction actions for 2018-2020.[3] In April 2019, it initiated a tax deduction policy to prompt nationwide corporations to participate in eliminating poverty. Previously, tax deductions for total charitable donations were limited to 12% of the annual profit. The new tax policy stipulated that corporate donations to registered poverty were fully tax-deductible (1) if donations are made towards government-targeted registered poverty, and (2) if donations are made through the county level or a higher level of government or through their directly affiliated institutions and social organizations. The program was initially set to end in 2022 but then extended to 2025.

[3] See https://www.gov.cn/zhengce/2018-08/19/content_5314959.htm. (in Chinese) last accessed on 17 July 2024.

At this juncture, we can see the tripartite relationship emerging. The central government would only qualify donations as tax deductible for those targeting the poverty registry population. As such, firms feeling compelled to support the central government's initiative had to access information on the poverty registry. However, these firms also needed the local governments' facilitation and approval to gain recognition and claim tax deductions.

B. The Hierarchical Central-Local Relations in China

Qian and Xu (1993) first suggested that since 1958 China's central government has used a multi-divisional structure to manage the country. In essence, China relies on a hierarchical governance system to coordinate the work between its central and local governments. (See also Li (1998) and Xu (2011)). This administrative structure works like a "one-principal-multi-agents" framework: the central government acts as the principal, and local authorities are multiple agents that run a partitioned Chinese economy. The central government sets-up policy initiatives, leaving local governments substantial autonomy to develop their regions accordingly (Qian & Xu 1993; Wang et al., 2020). Yet, the central government, via the Communist Party, controls cadres' careers and monitors them, thereby influencing the lower government's behavior.[4] It can take disciplinary actions against cadres for undesirable behaviors. It can also use promotion to incentivize local government officials to act in its interest. The extant literature uses this framework to explain China's economic performance from 2000 onward (e.g., Qian & Xu, 1993; McGregor, 2010; Li & Zhou, 2005; Xu, 2011).

Morck and Yeung (2018) expanded the framework to incorporate state-owned enterprises (SOEs) and banks as additional government levers to attain economic goals. Other

[4] See McGregor (2010). Note all senior government officials are communist party cadres.

important instruments include a shared fiscal and tax system, SOEs, state-controlled banks, and regulatory and supervisory bodies, all initiated by Premier Zhu (1998-2003) (see Bai et al., 2016; Morck & Yeung, 2018). Deng et al. (2015) use this expanded framework to explain China's ability to use a huge monetary expansion to generate economic growth amid the great financial recession in 2008. These pieces emphasize the role of enterprises in attaining government economic goals.

The TPA, with its 2019 tax deduction program, followed the same governance paradigm: a hierarchical tripartite central-local-government and corporation collaboration. However, the TPA added poverty reduction as a central government policy objective. Since the beginning of 2019 the TPA comprised (i) the central government's emphasis on reducing poverty, (ii) tax deductions to incentivize corporate participation, and (iii) local governments' facilitation and gatekeeping to channel corporate spending to help impoverished people listed on the Poverty Registry. The outcome of this modified hierarchical tripartite collaboration – assuming that the legacy emphasis on economic growth is still effective, deserves a detailed investigation.

In this hierarchical tripartite collaboration, local governments function as (i) information facilitators for corporate spending on reducing poverty, and (ii) approval agents for tax deduction applications. There could be a conflict of interest in the local government’s role. Corporate tax deductions will reduce a local government's fiscal revenue. Wu et al. (2014) illustrate that Chinese city-level governments are keen to build their fiscal revenues and spend on projects that promote economic growth. The reason is that local officials perceived economic growth as the primary means for career advancement. Even in the context of a modified

paradigm, such as in the TPA, local government officials are still incentivized to value fiscal revenue. However, recognizing tax deduction applications as successful as in the TPA would reduce fiscal revenues, hence muting performance on this key evaluative dimension.

Next, we investigate the key mechanisms of TPA's workings. We begin by focusing on how corporations responded to the central government's call to action. We investigate how the interests of local governments and corporate dominant controlling shareholders affect corporate donations. We then examine the validity of two critical assumptions in the modified hierarchical tripartite collaboration: (i) local governments might not fully embrace the central's new policy priority, and (ii) tax deductions are an auditing device that both prompted firms to align with the TPA but also checked if these same firms supported the central's new policy agenda. Then, we delve into the effect of corporate donations in reducing poverty, particularly in comparison to comparable levels of government spending.

III. DATA AND SUMMARY STATISTICS

A. Data and Sample

We collect and merge data from different sources to construct our sample. First, our firm-level data comprises all public firms listed on the Shenzhen or Shanghai Stock Exchanges from 2016 to 2020.[5] The firm-level data on financial information, board characteristics, and anti-poverty actions comes from the China Stock Market and Accounting Research Database (CSMAR), maintained by the GTA Information Technology Co., Ltd. Second, we retrieve local

[5] We stopped in 2020 because the central government's 2020 declaration of successfully eliminating poverty critically affected data collection and the behavior of corporations and local governments. Also, COVID-19 started to affect various spots in China's economy in the latter half of 2020, which would impact on the recorded distribution of poverty in 2021.

government-level fiscal data and demographic data, including poverty population and designated poverty counties, from the China Yearbook of Household Survey (2021 version, compiled by the National Bureau of Statistics of China), CSMAR, and Chinese Research Data Services. The designated poverty counties are the 832 key counties the Chinese central government specified as among the most poverty-stricken. We cross-validated data on provincial-level economic and demographic data between CSMAR and China Statistical Yearbook(s)[6]. We drop observations that have missing information on key variables of interest.

B. Variables

To examine corporate anti-poverty actions, we collect the CSMAR-provided data on "cash and in-kind" firm-level annual donations to registered poverty from 2016 to 2020. (The 2019 policy allows total tax deductions only for this type of donation.) We take the logarithm of this amount (plus one, as some firms report 0 for donations) to make the error term more homoscedastic[7]. In the Robustness Check section, we introduce and discuss alternative measures.

Our treatment indicator, *Policy*, divides the data window periods into the pre-*Policy* and post-*Policy* segments: *Policy* equals one if the year of an observation is 2019 or after; and zero otherwise. The dummy indicates tax deductions allowance.

We expect dominant shareholders significantly influence firm anti-poverty behaviors. We, therefore, differentiate firms according to their dominant shareholders: CSOEs, LSOEs, and POEs. The central government predominantly controls CSOEs, and local governments

[6] The two datasets yield identical information on provincial-level corporate tax revenue. Also, they yield very similar information about provincial-level population size, with only marginal discrepancies, due to slight difference in their methods to obtain the population size. Our cross-validation strengths our data quality and provides confidence on its reliability.

[7] Chen & Roth (2024) advise against interpreting a change in the so-transformed dependent variable as percent change and against using the transformation on extensive margins. We acknowledge these issues. Our work focuses on the magnitude of donations, especially in how the magnitude is related to the type of firms. The transformation is for mitigating the effect of large magnitude observations on our regression coefficients and the donation spending measures intensive margin.

predominantly control LSOEs. POEs will first and foremost cater to their dominant owners.

We designate a firm as *Central SOE* if either the central government or its directly associated affiliations predominantly control a company, defined as (1) holding more than 50% of the company's shares; or (2) controlling more than 30% of the company's voting rights; or (3) determining the appointment of more than half of the company's board of directors; or (4) controlling sufficient shares to have a clear impact on the resolutions of the company's shareholders' meeting; and zero otherwise[8]. *Local SOE* equals one if a local government or its directly associated affiliations predominantly control a company as defined above and zero otherwise. The reference group is POEs, which are predominantly controlled by neither the central nor local governments nor their affiliates.

We include a series of control variables that we expect to affect a firm's inclination to make anti-poverty donations. At the firm level, we control for *Asset* (the logarithm of total assets), *ROA, leverage* (total assets/equity), *Market-to-book ratio, Earnings volatility* (measured by the volatility of (EBIT/Assets) of the past three years), *Surplus reserves* (firm's reserves against losses, taking the natural logarithm), *Board Gender* (fraction of board members who are female), and *Board interlock* (measured as 1 if a firm had at least one board member serving on the board of any of the other firms that donated to reduce poverty, in a given year). We also control for environmental conditions that affect firm donations: *Local government education expenses* (the logarithm of fiscal expenses on education at city-level) and the lagged year's GDP per capita growth rate.

[8] According to Article 84 of Regulations on the Takeover of Listed Companies, control rights, by definition, satisfy any of the four circumstances listed here. Notably, control rights also exist under certain circumstances deemed by the China Securities Regulatory Commission. However, the regulations did not specify or elaborate the special circumstances.

We winsorize all continuous variables at the first and ninety-ninth percentiles to ensure that outliers do not drive our results. We note our results are also robust without winsorizing. Unless we state otherwise, we express all monetary values in ten thousand CNY to interpret the results consistently.

C. Descriptive Statistics

Table 1 panel A presents descriptive statistics of all key variables used in the main analysis. We partition the sample into three sub-groups: CSOEs, LSOEs, and POEs. All three sub-groups of firms have comparable average asset size and ROA. POEs have lower leverage, higher earnings volatility, higher market-to-book value, more female board members, and less interlocked membership that might induce anti-poverty donations. On average, CSOEs make more anti-poverty donations, and POEs the least, a point consistent with the patterns of the year-by-year average donations by firm types measured in raw amounts, scaled by firm-level total assets and by national-level GDP shown in Panels B, C and D in Table 1. We note, however, that while POEs' average donation is the least among the three types of firms, their total donation exceeds that of SOEs. (The ratio of numbers of POEs, LSOEs and CSOEs are roughly 68%: 21%: 11% across the years.) Figures II A and B show the total and average donation by firm type based only on firms that have donated.

IV. BASELINE RESULTS

A. Determinants of Firm-Level Donations after the Tax Deductions Policy

We begin the empirical analysis by analyzing how different firm types responded to the 2019 tax deduction policy by employing a province and industry fixed-effects ordinary least squares

(OLS) model with robust standard errors clustered two-ways at the year- and location-level as follows[9]:

$$Log(anti\text{-}poverty\ donation+1)_{itjk} = \alpha + \beta_1 \cdot Policy_t \times Central\ SOE_i + \beta_2 \cdot Policy_t \times Local\ SOE_i + \beta_3 \cdot Policy_t + \beta_4 \cdot Central\ SOE_i + \beta_5 \cdot Local\ SOE_i + \gamma \cdot Control + Province_k + Industry_j + \epsilon_{itjk} \quad (1)$$

Dominant Stakeholder's Preferences

Managers' perspectives can influence donation patterns in three types of firms, as they cater to their dominant stakeholders. CSOE and LSOE managers have dual mandates: supporting government policy agendas while delivering business returns (Bradshaw et al., 2019; Deng et al., 2015). The central government can directly affect CSOE managers' careers, while the local governments have the same influence over LSOE managers. However, the central government likely values corporate spending on reducing poverty more than local governments. Consequently, given the varied incentives of the controlling shareholders, CSOE managers will lead their companies to donate more resources to fight poverty in response to the 2019 TPA program than LSOE managers.

In contrast, POE managers, answer to their stakeholders, who are in the private sector, are less driven to respond to the TPA program, as they seek to avoid revealing profitability and face less pressure to participate.

In addition, tax deductions appeal more to CSOE and LSOE managers due to higher effective tax rates their companies paid (Bradshaw et al., 2019), while POEs, wary of political risks, stay away from participation. Lastly, SOEs benefit from government ties, having easy access to poverty registry information and tax deduction opportunities, whereas POEs face

[9] We acknowledge the challenges in using the transformation in footnote 10. In the robustness section below, we discuss using a different format for the dependent variable and other econometric specifications.

higher search costs.

We investigate the hypothesis using the Equation (1). Table 2 reports our main regression results. Model 1 excludes the interaction terms, *Policy* × *Central SOE* and *Policy* × *Local SOE*. The results show that CSOEs make more anti-poverty donations in our sample years than POEs (Model 1, *Central SOE*: $\beta = 0.537$, $p < 0.05$). LSOEs donate more than POEs, but not significantly so (Model 1, *Local SOE*: $\beta = 0.215$, $p > 0.1$).

Model 2 shows affirmative results. Both CSOEs and LSOEs did not donate more than POEs before 2019, but both did afterward. The coefficients for *Policy* × *Central SOE* and *Policy* × *Local SOE* are 0.799 ($p < 0.01$) and 0.351 ($p < 0.1$), respectively. We also check that the former is statistically significantly greater than the latter. Notably, although the coefficient for *Policy* is not statistically significant ($\beta = 0.186$) at conventional levels, its *t*-value is 1.53 with a one-tail *p*-value of 0.1005, weakly supporting the possibility that the 2019 policy induces some private corporate anti-poverty actions.

These results indicate that CSOEs raised more donations than LSOEs after the 2019 policy, while POEs' reaction was marginally positive. The reasons are intuitively appealing[10]. Overall, the findings are consistent with the hypothesis that firms react to TPA according to their dominant stakeholder's interests.

Local Government's Affordability

Let us now turn to the government's perspectives, as we expect firms with local government fiscal success should respond more strongly to the 2019 policy. Local governments

[10] We note here that the reported regressions incorporate province- and industry-fixed effects, which absorb the influences of time-invariant provincial and industry factors. Our controls also remove firm-specific factors like size, profitability, indebtedness, potential needs for investment funds, earnings volatility, board characteristics, and peer influences.

need to balance keeping resources to pursue their policy agenda and following the central government's social policy agenda. In other words, local governments with lagged lower per capita corporate tax or fiscal revenue will be less encouraging of firms making tax-deductible donations. To delve into this possibility, we classify a firm's local government as having high (1) corporate tax revenue or (2) fiscal revenue if the per capita measure of these variables is above the sample median in the lagged year[11]. The corporate tax revenue is at the provincial level, and the fiscal revenue is at the city level.[12] We use the median to divide the samples and repeat Model 2. Table 2 Models 3 and 4 report the results of the sub-sample regression analysis using the median of lagged corporate tax revenue per capita variable to split the sample. Similarly, Models 5 and 6 report the analogous results using the lagged median fiscal revenue per capita variable to split the sample.

Results in Models 3 versus 4 show that both CSOEs and LSOEs, responding to the 2019 tax deduction policy, increased their tax-deductible donations less in provinces with a low corporate tax revenue indicator[13]. Similarly, Models 5 versus 6 show that both types of firms increased their tax-deductible donations less in cities with a low fiscal revenue indicator.[14] We follow prior research to test if these coefficients are statistically different across sub-samples (Cleary, 1999). Adopting both the bootstrap and permutation test procedures (1000 times), we obtain a distribution of the β's. The distributions allow us to determine the p-values of the

[11] We obtained qualitatively similar results by using the concurrent indicators of local governments' economic performance indicators. We do not report these results to conserve space.

[12] We also normalized the two measures based on the location's annual GDP for robustness checks. We obtained qualitatively similar results.

[13] Model 3, *Policy × Central SOE*: $\beta = 0.577$, $p < 0.05$ vs. Model 4, *Policy × Central SOE*: $\beta = 0.951$, $p < 0.01$; Model 3, *Policy × Local SOE*: $\beta = 0.125$, $p > 0.1$ vs. Model 4, *Policy × Local SOE*: $\beta = 0.602$, $p < 0.05$.

[14] Model 5, *Policy × Central SOE*: $\beta = 0.684$, $p < 0.01$ vs. Model 6, *Policy × Central SOE*: $\beta = 0.950$, $p < 0.01$; Model 5, *Policy × Local SOE*: $\beta = 0.176$, $p < 0.1$ vs. Model 6, *Policy × Local SOE*: $\beta = 0.663$, $p < 0.05$.

observed differences in the split-sample coefficient estimates. They are reported in the rows, '*Tests of coefficient differences'* in Table 2[15]. The results confirm that these coefficients from the subsamples are significantly different. These results indicate that firms varied their anti-poverty actions according to their local governments' affordability to sacrifice corporate tax income.

Central Government's Information and Monitoring

Following the same thinking, we expect that the central government's awareness of a firm's responses to its policy agenda will matter; tax deductions could be the central government's monitoring device (Slemrod, 2019).

We delve further into the central government's awareness of corporate support of its anti-poverty policy. Two obvious factors that heighten the central's awareness would be analyst following and a company's presence Beijing, the capital city. We capture analyst following by (1) the number of security analysts following and (2) the number of analyst reports issued to the firm. Users may need time to learn about the analyst following condition, and to mitigate endogeneity; we used one-year lagged indicators of analyst following and analyst reports.[16] We split the sample by the median level of these variables and re-run Model 2. We capture a firm's *presence in Beijing* by whether the firm has at least one office in Beijing.

Table 2, Models 7 and 8, report supportive results based on splitting the sample into above and below median *analysts following*: CSOEs and LSOEs in the former subsample increased their tax-deductible donations in response to the 2019 tax deductions policy more

[15] The *p*-value tests are based on the null hypothesis that the coefficients are equal for the two split samples.

[16] We obtained qualitatively similar results by using the concurrent indicators of analyst following. We do not report these results to conserve space.

than their counterparts in the latter sub-sample.[17] Likewise, Models 9 and 10 show that firms receiving more analyst reports also increased their donations more in response to the 2019 tax deductions policy[18]. We calculate empirical *p*-values on coefficient differences by both the bootstrap and permutation test (1000 times) and confirm that the coefficients significantly differ between the subsamples. These findings indicate that the central government's access to firm-level information raises a firm's donations.

Table 2 Models 11 versus 12 show that, for both CSOE and LSOEs, a physical presence in Beijing raises their corresponding donations in response to the 2019 tax deductions policy.[19] The results indicate that the proximity to Beijing reduces the information asymmetry for the central government. This proximity raises the state's monitoring acuity and thus induces more anti-poverty donations for firms physically present in Beijing.

B. Robustness Checks

In this subsection, we summarize the robustness tests we conducted to augment the baseline econometric specification further or address potential threats to our baseline findings.

Robustness Test for Alternative Dependent Variables

First, we repeat the regressions without winsorizing the dependent variable; the results remain qualitatively similar.[20] Second, instead of examining the magnitude of donations (in the natural log), we explore anti-poverty donations relative to total assets. This alternative dependent variable is measured as log (1 + (donation amount measured in CNY /total asset

[17] Model 7, *Policy × Central SOE*: β = 0.531, p <0.05 vs. Model 8, *Policy × Central SOE*: β = 0.913, p <0.01; Model 7, *Policy × Local SOE*: β = 0.213, p >0.1 vs. Model 8, *Policy × Local SOE*: β = 0.496, p <0.05.

[18] Model 9, *Policy × Central SOE*: β = 0.561, p <0.05 vs. Model 10, *Policy × Central SOE*: β = 0.895, p <0.01; Model 9, *Policy × Local SOE*: β = 0.208, p >0.1 vs. Model 10, *Policy × Local SOE*: β = 0.518, p <0.05

[19] Model 11, *Policy × Central SOE*: β = 0.697, p <0.05 vs. Model 12, *Policy × Central SOE*: β = 1.102, p <0.01; Model 11, *Policy × Local SOE*: β = 0.292, p <0.1 vs. Model 12, *Policy × Local SOE*: β = 1.173, p <0.01.

[20] These results are available upon request but are not reported to conserve space.

measured in millions of CNY)). Table 3 reports these results, which are qualitatively similar to the main results reported in Table 2.

Second, we construct a dummy variable that equals one if a firm donated to registered poverty in a given year and zero otherwise. We use this dummy variable as an alternative dependent variable in the equation (1) and run a linear probability model, which is advantageous in result interpretation and accounting for fixed effects. The results are consistent with our main analysis; CSOEs are the most likely and POEs the least likely in making anti-poverty donations, after the 2019 tax deduction policy as incentivization. These results are generally more pronounced with local government fiscal success, analyst following and proximity to Beijing. We thus find qualitatively similar results to our main analysis.

Robustness Test for Alternative Samples

Entering and exiting firms could behave differently than ongoing concerns. Exiting firms may not have full control of their corporate resources, and entering firms may be particularly eager to meet the central government's expectations. We eliminate this noise by excluding the firms with entry or exit experiences from 2016 to 2020. The test results remain qualitatively similar. However, these test results are not included to conserve space.

Robustness Test for Alternative Local Government's Affordability Indicators

We scale the total corporate tax revenue at local-government levels by provincial annual GDP to avoid inadvertently allowing a location's income to affect our result. If the location is a city, we scale by the city's GDP. Our results remain qualitatively similar.

Robustness Test for Alternative Model Specifications

Instead of conducting sub-sample analyses, we create indicator variables for the low versus

high measures of a location's economic performance. The dummy variable takes a value of one if a firm has above the yearly sample median of a local government's economic indicators and zero otherwise. We also use an indicator variable for a firm's analyst following constructed similarly. The dummy takes a value of one if a firm's analyst following is above the median number of analysts and zero otherwise. Likewise, we develop a dummy to indicate if a firm has a physical presence in Beijing. We then perform a three-way interaction analysis for each of these dummies to test if the anti-poverty donations elicited by the 2019 tax deduction policy are modulated by analyst following, domiciled location's economic performance, and presence in Beijing. The results are generally similar to our main specification.

We also use left-censored Tobit regression models because donations cannot be negative. These models yield statistically significant coefficients consistent with our OLS runs. Specifically, CSOE donations exceeded LSOE and POE donations. LSOEs donated more than POEs, but insignificantly. Consistent with our prior results, local governments cannot significantly influence POEs' donation actions but can after the 2019 policy. We note that the split-sample coefficients on high versus low analyst following are not statistically different. The indicators of a local government's economic performance and firms' physical presence in Beijing negatively moderate firm-level donations but are statistically significant only for LSOEs. This further strengthens the point that local governments are more able than the central government to pressure LSOEs to meet their local political agendas.

To mitigate the potential omitted variables issue, we conduct an alternative specification that includes both firm-fixed effects and year-fixed effects). In this alternative specification, we thus suppress the coefficients on firm-types (i.e., *Central SOE* and *Local SOE*) and the policy

indicator (i.e., *Policy*). We find the results are qualitatively similar for the rest of the key variables of interest (i.e., *Central SOE x Policy* and *Local SOE x Policy*) in all models, compared to Table 2. This robustness check thus mitigates the issue that the effect of time-invariant firm characteristics and time trends drive our key findings.

V. Checking critical assumptions of the mechanisms

A. Local vs. Central governments' priority on poverty reduction

A complication in the TPA program is that local governments value poverty reduction less than the central government. We validate the difference by directly examining how the central and local governments vary in giving awards to donating firms. Giving awards is a frequently used gesture in China and elsewhere to encourage specific firm actions. Awards from the government generate a positive social image and enhance a firm's reputation, financing opportunities, and even bargaining power. Results in Table 4, Model 1 show that a firm making anti-poverty donations significantly increases its likelihood of receiving awards from the government and other social associations[21]. Models 2 and 3 results show that only the central government gave significantly more awards to donations for poverty reduction after the 2019 policy; the local governments did not.[22] These results validate the difference in the intensity of the two levels of government in pursuing poverty reduction: while the central government actively encouraged corporate anti-poverty actions, the local governments were not as active, even after the central government intensified its poverty reduction efforts.

[21] Model 1, *Log (anti-poverty donation+1)*: $\beta = 0.030$, $p < 0.01$.

[22] Model 2, *Policy x Log (anti-poverty donation+1)*: $\beta = 0.006$, $p < 0.05$ vs. Model 3, *Policy x Log (anti-poverty donation+1)*: $\beta = 0.002$, $p > 0.1$.

B. Tax-deductions as an auditing and prompting device

Our baseline results are consistent with that the 2019 tax deduction policy elicits corporate spending on reducing poverty. While tax deductions provide monetary incentives, they also serve as a government audit check, this is because local governments rigorously ascertained that the forgone local tax revenue from deductions translated into tangible poverty reduction. This aligns with the idea that local governments intensify tax enforcement, especially when it directly impacts their local revenue (Chen et al., 2022). As the 2019 tax reduction program reduces local tax revenue, we want to use this setting to affirm further that tax deductions play an auditing role in desirable corporate behavior (Slemrod, 2019).

In doing so, we take advantage of the fact that poverty reduction is a legitimate part of corporate social responsibility (CSR). In 2008, China's stock exchanges issued CSR reporting guidelines for firms, reflecting the central government's emphasis on firm-level social responsibility (Chen et al., 2018)[23]. However, these institutional pressures can result in pretentious behavior: a firm may issue window-dressing CSR reports and initiate only trivial CSR efforts (Marquis & Qian, 2014). To unravel the auditing function of tax deductions, we ask two questions. (i) Do firms that issue CSR reports make donations to alleviate poverty? (ii) Does the 2019 tax deduction policy reduce window-dressing behavior: does the policy make talkers walk the talk?

In Table 5, we call a CSR reporting firm a talker if it has issued at least one standalone CSR report before 2019. Model 1 shows the regression results using CSR reporting firms, i.e.,

[23] China has required mandatory CSR disclosure for certain firms, such as for firms listed in the Governance Index, while encouraging other types of firms to disclose CSR-related information.

the talkers. Talking CSOEs, LSOEs, and POEs made insignificant donations before the 2019 Policy: they talked but did not walk. Afterward, the *Policy* dummy is statistically significantly positive, meaning these firms, even POEs, raise their donations for poverty[24]. And as expected, both talking CSOEs and LSOEs elevated their anti-poverty donations more than talking POEs, although only CSOEs did so statistically significantly.

Table 5, Model 2 shows the regression based on non-CSR report issuing firms. After the 2019 policy, non-talking POEs did not respond (Model 2, *Policy*: $\beta = 0.171$, $p > 0.1$), but non-talking LSOEs and CSOEs raised their donations to poverty. Finally, non-talking LSOEs donate to poverty more than non-talking POEs before 2019.

The results in Table 5 thus reveal that firms issuing CSR reports did not spend on reducing poverty until the tax deductions for donations policy was installed. Furthermore, the tax deductions policy does a prompting job: it also elicits donations from non-talkers to fight poverty, except for the non-talking POEs.

VI. FIRM ANTI-POVERTY APPROACHES

This section studies how firms target and direct their anti-poverty donations. Banerjee and Duflo (2011) highlight that the success of poverty reduction depends on identifying the driving causes of poverty. Donations to the impoverished might not lead to sustained poverty alleviation, e.g., if the root causes of poverty remain unchanged. In China's TPA program, Chinese firms' spending in helping poverty reduction was tax deductible only if the effort targeted households genuinely in need listed on the poverty registry. Furthermore, the registry included pre-

[24] Table 5 Model 1, *Policy*: $\beta = 0.455$, $p < 0.1$

designated anti-poverty actions tailor-made for each household on the list. It is, therefore, worthwhile to document what the corporate actions entailed.

We classify a firm's anti-poverty actions into six sub-dimensions according to targeted goals or objectives: (1) employment creation, (2) industrial development, (3) education, (4) health and environment protection, (5) basic needs, and (6) others. Table 6 Panel B reports their definitions. We then construct six dummy variables to represent if a firm undertook a specific action or donated to a particular category. For example, if a firm donated to resolve health and environment issues experienced by impoverished people, the *Health & environment dummy* equals 1, and 0 otherwise.

We regress these six dummy variables onto the set of independent and control variables as before. Table 6 Panel A shows that all corporate donors spent little on health and environmental issues. LSOE donations also missed "*Education*" and contributed more actively to "*Employment*" and "*Industry development*" to align to local government's priorities on short-term economic development goals. POE donations only focused on "*Basic Needs*", which deliver immediate solutions. CSOE, being most supportive of the central government's call to reduce poverty, made donations in all other categories except health and environmental actions.

We further group these six dimensions into three categories according to their economic nature: government economic responsibility, government social responsibility, and redistribution (see Table 6 Panel B). Table 6 Panel C Model 3 shows that state-owned firms responded to the 2019 policy by donating in all categories. Interestingly, all types of companies, even POEs, responded to the 2019 policy by donating to a category where the Chinese government often seemed to do little, i.e., the redistribution (to people) category. This also

suggests that corporate actions are strategically targeted in the right areas, potentially explaining why they are instrumental in achieving poverty reduction.

VII. THE AGGREGATE EFFECT OF CORPORATE ANTI-POVERTY ACTIONS ON SOCIETY

Our results show that the central government can use tax incentives to elicit corporate donations to combat poverty, especially in areas where Chinese governments did not do much in the past. The remaining question is the aggregate effect. Tax deductions for charity programs are equivalent to pre-committing government spending in designated areas, as directed by the private sector. Yet, government-directed and pre-committed private-sector-directed spending might vary in effectiveness. As for corporations, the economic impacts on earnings guide corporate spending on fighting poverty, whether on job training and creation or generally on creating economic opportunities. In contrast, government actions are often less result-oriented and more bureaucratic[25]. Therefore, we examine the comparative effects of government vs. corporate anti-poverty actions, both at the provincial and city levels.

A. Provincial level analysis

First, in Table 7A, we examine the effect of corporate anti-poverty donations on poverty reduction at the provincial level. Our dependent variable is the percent reduction in the poverty population ((poverty population in year $_{t-1}$ – poverty population in year $_{t}$) / poverty population

[25] According to the National Audit Office, in 2015, a total of 151 million CNY of poverty alleviation funds were fraudulently claimed or misused. For example, some local governments made fake documents, including duplicate poverty register applications, to claim more funds. Some local governments misused the funds as directed to fiscal budgets and other expenditures, like municipal construction, hotel renovations, and operation expenses. A total of 870 million CNY funds were wasted due to inappropriate fund coordination by local governments. Refer to https://www.audit.gov.cn/n5/n26/c84918/content.html. In Chinese. Last accessed on 17 July 2024.

in year $_{t-1}$).

Our key independent variable is the sum of firm-level anti-poverty donations at the province-year level. Before summing the firm-level observations, we winsorize the variable at the first and ninety-ninth percentiles so that outliers do not drive our results.

To examine different governments' anti-poverty actions, we first include provincial government expenditures marked for reducing poverty (Ravallion & Chen, 2007) as independent variables. We next include the central government's transfer to a province to reduce poverty. (Considering that local government may artificially raise the poverty count to obtain more central government fund allocation, we expect that the granted central government fund would still be an explanatory variable for a future reduction in the poverty population.)

To consistently interpret the results, we scale all corporate, provincial, and central government expenditures by the size of the poverty population in the lagged year. These independent variables are all expressed in their natural logarithm.

We augment our specification in several ways. We include the growth rate in GDP per capita to control for the generic trend that economic growth allows even those in extreme poverty to raise their living standards. Due to the spurious simultaneity between poverty reduction and per capita GDP growth, we use the lagged per capita GDP growth. We compute the lagged growth in per capita GDP as ((GDP per capita in year $_{t-1}$ – GDP per capita in year $_{t-2}$) / GDP per capita in year $_{t-2}$). We also control for provincial fixed effects and cluster the standard errors by province and year. We exclude the 2020 data for robustness as this is the year that the National Bureau of Statistics of China claimed that China had eliminated poverty and all poverty numbers went to zero.

Corporation effects

Table 7A, Model 1 presents the results. The marginal effect of corporate-level donations on poverty reduction declines statistically insignificantly after the 2019 Policy.[26] This reflects diminishing returns as corporate donations have increased.

The regression coefficient in Model 1 for the impact of *Log(corporate anti-poverty donation/ poverty $_{t-1}$)* on poverty reduction is positive and statistically significant ($\beta = 0.055$, $p < 0.1$). Thus, the effect of a 10% increase in corporate donations is 0.55% poverty reduction. In 2019, the province with the largest *Log(corporate anti-poverty donation/ poverty $_{t-1}$)* is Ningxia, which had a 13.49 percent reduction in the poverty population. Similarly, the province with the lowest *Log(corporate anti-poverty donation/ poverty $_{t-1}$)* is Jilin, which had a 1.18 percent reduction in the poverty population.[27]

In addition, the *Policy* dummy has a statistically significant coefficient of 0.392 indicating an average reduction of 39.2 percent in the poverty population across provinces. The result indicates that the 2019 policy intensified poverty reduction nationwide.

Putting these numbers together, we judge corporate donations play an economically significant role in reducing poverty.

Government effects

In Model 1, all government expenditures and per capita GDP growth are insignificant in explaining poverty reduction. The lack of impact on poverty reduction by the central government fund allocation on poverty reduction is noteworthy. First, the observation casts

[26] Model 1, *Policy x Log (corporate anti-poverty donation/ poverty $_{t-1}$)*: $\beta = -0.043$, $p > 0.1$.

[27] In our sample, in 2019, *Log(corporate anti-poverty donation/ poverty $_{t-1}$)* for Ningxia and Jilin are 7.059 and 2.677, respectively. Also, the sample-period provincial average of *Log(corporate anti-poverty donation/ poverty $_{t-1}$)* for Ningxia and Jilin are 4.606 and 2.462, respectively.

doubt on the effectiveness of TPA relying on government efforts alone. Further, it adds credence to the validity of the number of impoverished people on the poverty registry. Local governments could have exaggerated the local poverty situation to obtain more central fund allocation. If that were the case, the higher the central fund allocation, the greater the subsequent poverty reduction should be, which we do not observe.

Robustness checks

In our provincial-level runs, the number of observations is limited, and collinearity can be a problem. We, therefore, run Model 2 to mitigate collinearity by keeping only the *Policy* dummy, corporate donations, and the lagged per capita GDP growth. In Model 3, we add the government expenditures variables but skip the government revenue. In Model 4, we add the government revenue back but skip the government expenditure variables. All these added variables are insignificant except for the local government expenditure on social security and employment in Model 3 and the government revenue in Model 4. The policy and corporate donations variables behave like in Model 1.

Counterfactual analysis

The regression results allow us to make counterfactual comparisons: If the government disallows tax deductions, it could collect more fiscal revenues for social programs. We thus ask: would allowing the government to spend these additional taxes be more effective than corporate donations in reducing poverty? Specifically, we first aggregate the possible incremental corporate tax revenues to the province-year level. Then, based on our regression results in Table 7, we calculate the differential impacts on poverty reduction: comparing poverty reduction due to corporate donations versus letting the provincial government spend the incremental taxes on

its most effective means of poverty reduction.

We calculate the forgone impact of poverty population alleviation in 2019 using Table 7A Model 3. We adopt that model because we see a government expenditure can explain poverty reduction significantly, which is (Log_e(Local government expenditure on social security and employment/$poverty_{t-1}$)). The impact of the donations, based on the coefficient of Ln(corporate anti-poverty donation/$poverty_{t-1}$), is 30.69 percent (= ln(327.2815) x 0.053 where 327.2815 is the post-policy sample average of (corporate anti-poverty donations/$poverty_{t-1}$). If all these donations were canceled, the incremental in government tax revenues scaled by the lagged year poverty size is 327.2815 x 25%[28] x 40%[29]. To maximize the incremental gain in poverty deduction, we assume the incremental tax revenue was all spent on social security and employment expenditure, the only category of government expenditure that significantly explains poverty reduction. The resulting incremental gain in poverty reduction is around 0.001%, which is extremely marginal. Obviously, the forgone poverty deduction (as if the corporate donations were canceled) substantially outweighs the gained poverty reduction (as if the tax deductions became tax-paid and local governments spent the incremental all on poverty reduction); this illustrates the impressive impact of corporate actions in reducing poverty.

B. City level analysis

Table 7B presents additional results based on city-level data. In 2011, the Chinese central government listed the 832 most poverty-stricken counties as key "registered poverty counties". The central government gave them the highest priority in its poverty reduction efforts.

[28] The corporate income tax applies a rate of 25% to business entities in China, while certain firms can enjoy a lower rate, e.g., key high-tech enterprises that received the government support.

[29] After 2002, generally, the central government receives 60% of tax revenues and local governments receive 40% (Bradshaw et al., 2019).

These counties' exits from the list warrant further analysis to understand the extent to which a local government and listed corporations aligned their efforts to the central government's anti-poverty goals.

In this analysis, the dependent variable is the percent reduction in a city's number of designated poverty counties. We collected information on the year when a designated county exited the poverty designation. We then calculate the percent reduction in designated counties at the city-year level.

Our key independent variable is the sum of firm-level anti-poverty donations at the city-year level. We also include the effect of local government's spending on education and R&D in our regression. These variables are normalized by the lagged total population and expressed in their natural logarithm. In addition, we also control for the lagged per capita GDP growth rate, and provincial fixed effects and cluster the standard errors by province and year.

Corporation effects

Models 1 to 4 in Table 7B resemble the specifications in Models 1 to 4 in Table 7A. The results support the idea that corporate donations reduce poverty. The cross term of the policy dummy and corporate donations is negative but insignificant, suggesting a minimum decline in the marginal effectiveness of corporate donations in poverty reduction after the 2019 tax deduction policy.

Government effects

The variables of government revenues and expenditures remain insignificant. However, the lagged per capita GDP growth becomes significant. This result is expected as economic growth creates more economic opportunities and raises incomes for the impoverished

population. The result naturally appears when we use the more refined city-level data instead of aggregating data to the provincial level.

Robustness checks

Unsurprisingly, many locations with designated poverty counties may have no listed companies. Out of 166 cities with designated poverty counties, 66 have no corporate tax payable and donation records during our sample period. We designated them as cities with no listed firms. We repeat Models 1 to 4 in two subsamples – one that includes only locations with listed companies and one without. The results are reported in Models 5 to 8 and Models 9 to 10, respectively. The results in Models 5 to 8 reinforce those in Models 1 to 4. That is, corporate donations help to reduce poverty; furthermore, poverty reduction accelerated after the 2019 tax deduction program. Models 9 to 10 show that locations with no listed corporations also find that poverty reduction has intensified in 2019. In these sub-sample analyses, local government expenditure on education explains poverty reduction.

Counterfactual analysis

We apply the above calculation using Table 7A Model 3 to Table 7B Model 5. Corporate donations reduce the poverty rate by 4.29 percent. If corporate donations were not made, and the incremental tax revenue was added to the most effective government anti-poverty expenditure (i.e., the education expenditure), poverty reduction gains a very marginal 0.001%. The calculation again illustrates that corporate anti-poverty efforts are much more effective than government efforts in reducing poverty.[30]

[30] This footnote shows the calculation in greater details. The average of (corporate anti-poverty donation/ population $_{t-1}$) is 3.185 for all sampled cities after the policy. We express this value in a natural logarithm and multiply the log value by the coefficient 0.037 (the coefficient of Log(corporate anti-poverty donation/ population $_{t-1}$)). The impact of poverty reduction by corporate donation is thus 4.29 percent. Second, the increase in government tax revenues scaled by population size in the lagged

These observations validate the potency of getting corporations involved in fighting poverty within China's hierarchical central-local-corporation tripartite collaboration. Corporate spending on reducing poverty is targeted to give a durable lift because it easily motivate a corporate to do what a company does as a normal course of business, e.g., job training and creation and sustainable economic opportunities. Furthermore, corporate spending is pragmatic: guided by the economic impact on earnings. Government spending on reducing poverty is a transfer and not necessarily result-oriented and can be hindered by bureaucracy. Yet, the targeted corporate efforts are incentivized by tax deductions and local governments' facilitation in pin-pointing the efforts on the needy.

VIII. DISCUSSION AND CONCLUSION

This paper documents China's record against poverty following the central government's initiation of the TPA program. China's public governance is a hierarchical one-principle multiple-agent framework, as first depicted in Qian and Xu (1993). Deng et al. (2015) show that the framework also includes reining in a properly incentivized corporate sector. The extended framework works well when economic goals are prioritized. It produces growth when growth is preferred, but inequality follows. Amazingly, the framework also works when the policy priority includes reducing poverty. Our paper shows how China's central-local-corporate tripartite framework effectively delivers this added policy target. We believe the corporate sector plays a critical instrumental role in generating speedy growth and reducing poverty.

year is 3.185 x 25% x 40%. We add this value to the average of (local government expenditure on education expenditure/population $_{t-1}$) for all sampled cities after 2019. After comparing the initial and newly added effect of education expenditure on poverty reduction, we observe the incremental poverty reduction is around 0.001 percent.

The key mechanisms of the TPA are task and incentive alignment, which induce preferred actions. Initially, the central government gave clear policy directions and assigned local governments (as its agents) to create a poverty registry. This registry informs government and corporate anti-poverty efforts. While the central government assigned multiple objectives (poverty reduction objectives simultaneously with economic growth objectives), it did not add instruments to enable the local governments to pursue all objectives. To engage corporate sector, the central government added the 2019 tax deductions policy to incentivize corporations to participate in accelerating poverty reduction. Our empirical results show that this modified hierarchical tripartite led to targeted efforts with success.

Interestingly, the special central government funds transferred to local governments designated for poverty reduction showed no directly observable effect on poverty reduction. One possibility is that the central fund allocation is a substitute for local fund allocation in fighting poverty. Another possibility is that corporations are more effective than bureaucrats in reducing poverty as corporations can invoke more local-specific measures and more economic result-oriented. Our counterfactual calculations based on our regression results confirm this conjecture.

Unlike traditional social welfare programs, China's TPA adopts a development-driven approach aided with detailed and collated information to help the corporate sector to provide employment and industry development opportunities, which could help reduce poverty even after the donations end. Additionally, the tax deduction program serves as an auditing function in China. Before the tax deduction was available, many firms claimed to support CSR guidelines, but these firms had not taken authentic actions. After the program was installed,

these firms made genuine donations. Tax deductions make it hard for firms to "talk but not walk," aside from mitigating the donation cost. As an auditing means, this implies that a tax deduction effectively induces firms to show verifiable support for the central government's poverty elimination policy.

This paper offers policy implications for the trade-off between allowing corporate tax deductions and corporate tax revenues in exchange for direct private-sector spending on a targeted social objective. This thinking deviates from a Miltonian assumption of a perfect division of labor – companies aim to make profits and pay corporate income taxes, and governments collect taxes to finance public spending (Agénor et al., 2008) on, e.g., infrastructure, education, defense, and social services. The decision on whether to implement a tax-deductible anti-poverty donations program should incorporate considerations that include the effectiveness of direct corporate spending on attaining a policy target (relative to the government), corporations' incentives to participate, the government's ability to facilitate and audit targeted spending.

Our study has limitations. One key concern is the poverty registration data. The local governments in rich locations may not pay enough attention to the poverty elimination program, and their registrations may be unreliable. The local government may also inaccurately report the data when the central government emphasizes poverty reduction, albeit such misreporting is complicated given the depth of data and processes required for authentic reporting. That said, we believe we have used the poverty reduction program to provide a timely assessment of the positive result of the tripartite collaborative efforts of China's central and local governments and the business sector, especially the business sub-sector that the governments control.

The second key concern is the danger of adding key performance indicators to the M-form hierarchy. Our work suggests that making poverty reduction an open government policy objective can alleviate inequality. Yet, we have not investigated how this additional KPI affects China's growth performance. We must be wary that overloading local governments with KPIs can counterproductively affect China's overall economic performance.

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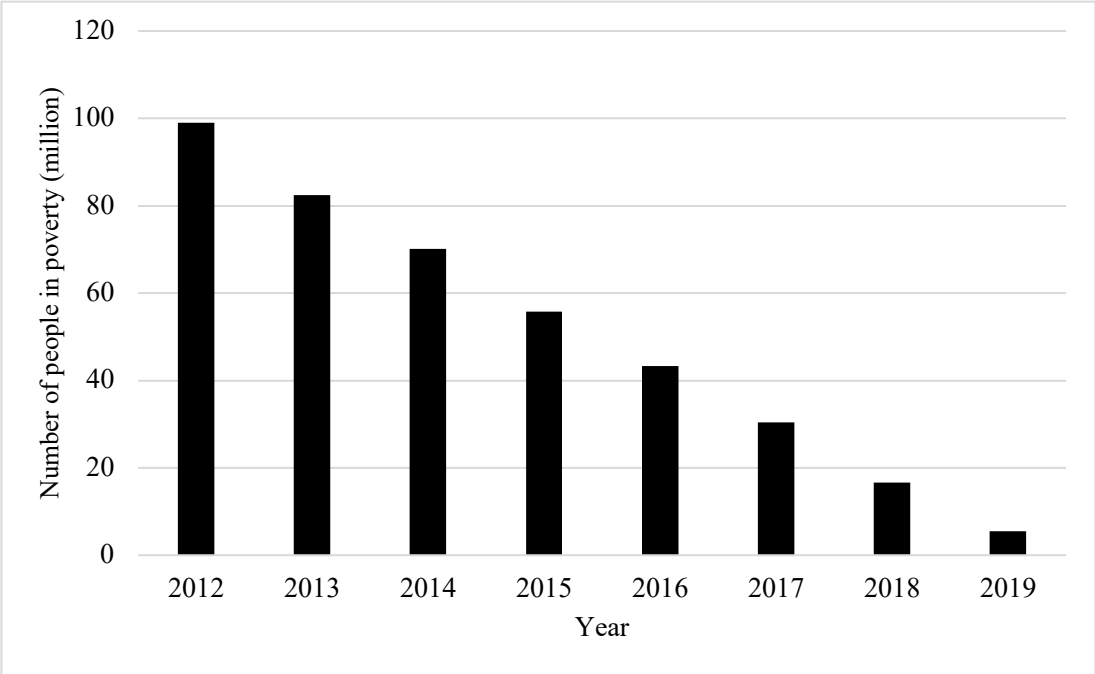
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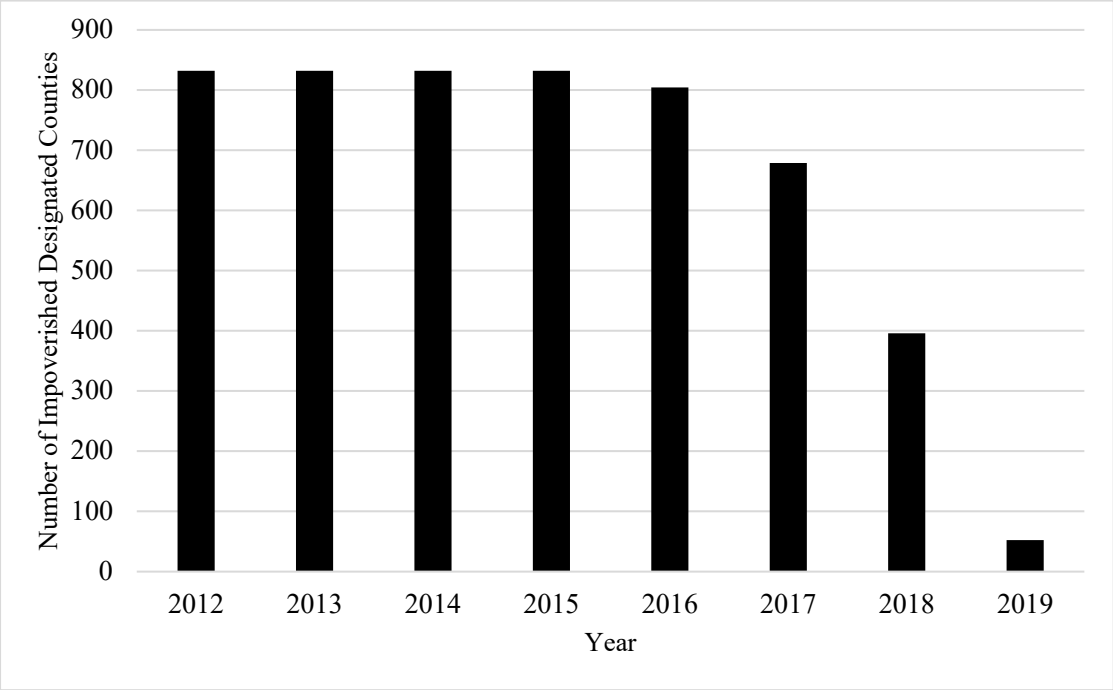
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Figure IA: The number of people in poverty (2012 to 2019)



Source: The State Council Information Office of the People's Republic of China, April 2021

Figure IB: The number of impoverished counties in the poverty registry (2012 to 2019)



Source: The State Council Information Office of the People's Republic of China, April 2021

Figure IC: Median provincial poverty population reduction rates (2011 – 2019)

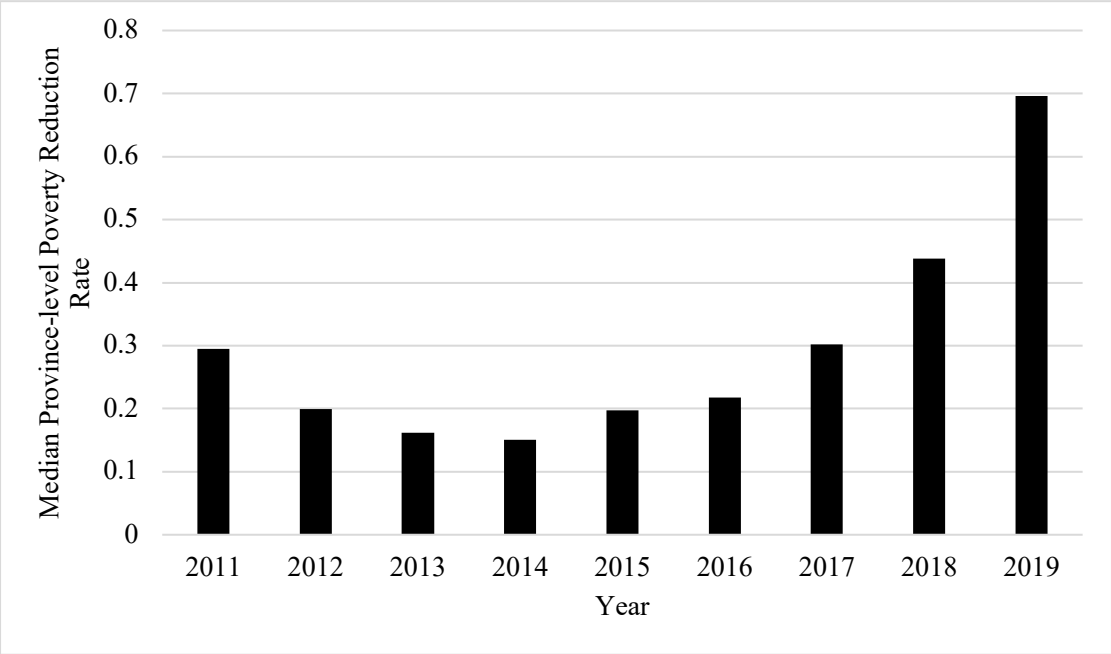


Figure IIA: Total corporate anti-poverty donations

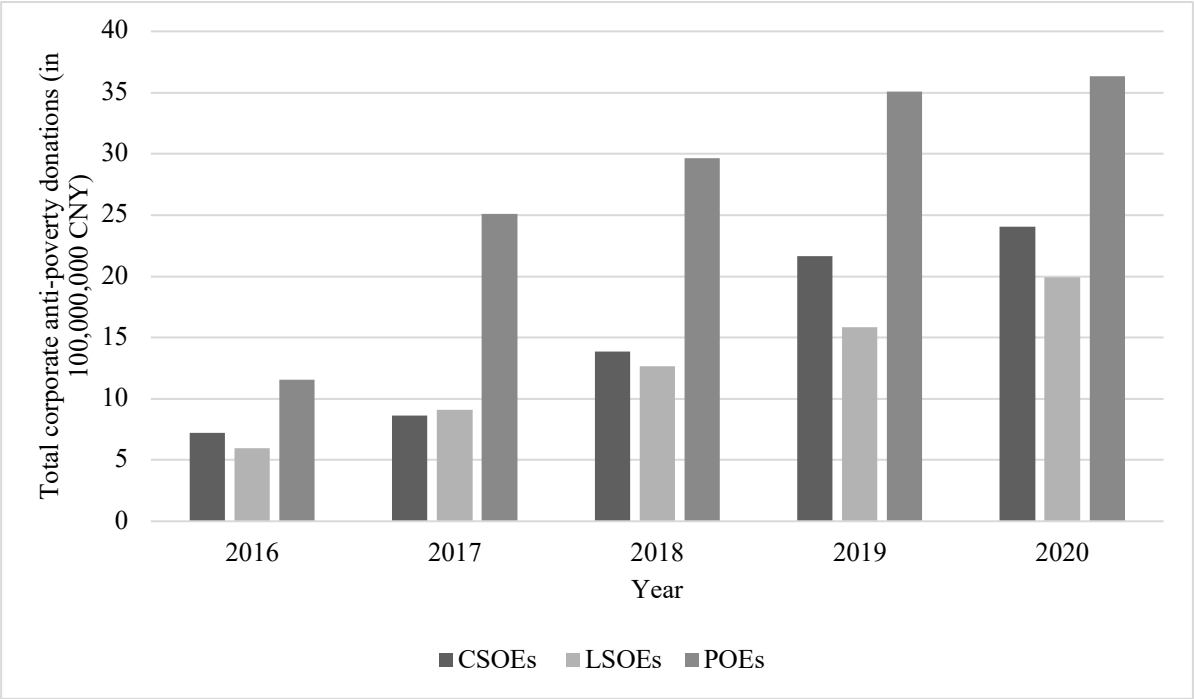


Figure II B: Anti-poverty average donations per firm type for donating firms

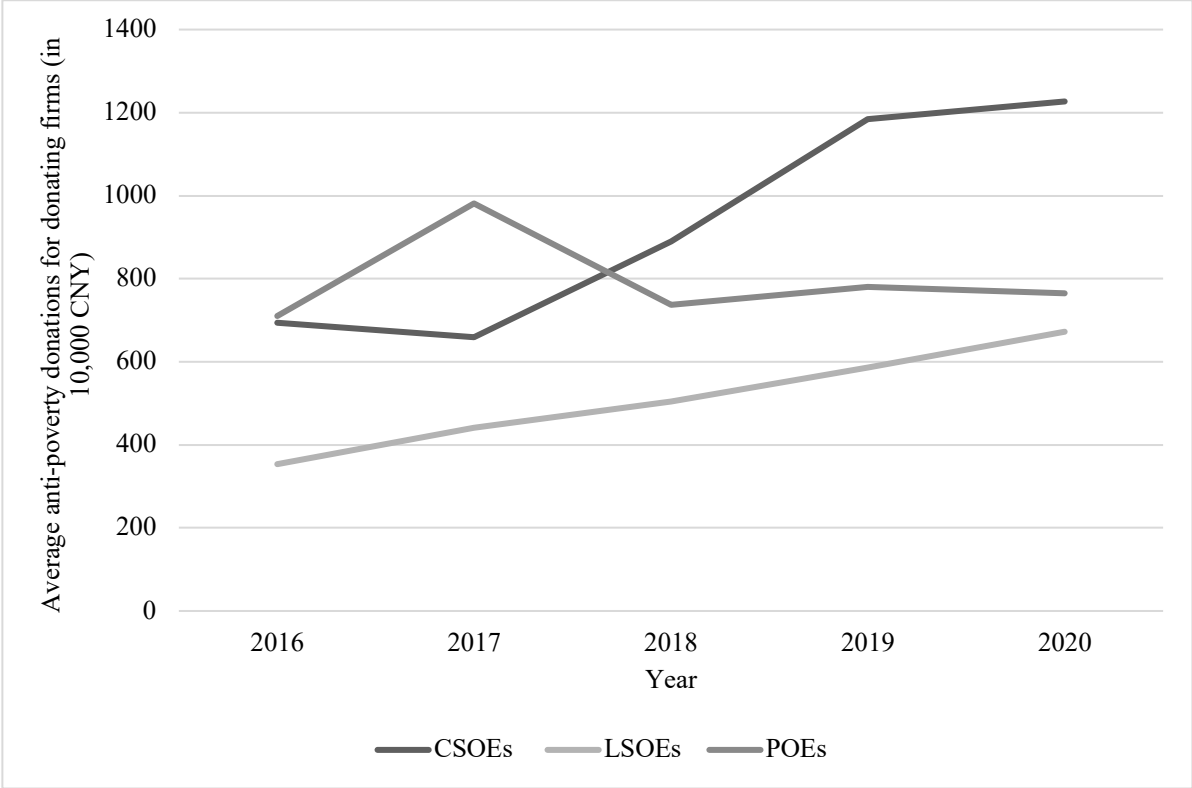


Table 1. Summary statistics and correlation matrix

Panel A. Summary statistics

Statistics	Log (anti-poverty donation+1)	Asset	ROA	Leverage	Market to book ratio	Earnings volatility	Board gender	Local government education expense	Surplus reserves	Board interlock	Lagged GDPPC growth
						POEs					
Mean	0.84	12.80	0.03	1.99	2.18	0.05	0.17	14.59	8.84	0.32	0.08
SD	1.99	1.15	0.10	1.46	1.46	0.07	0.13	1.02	1.08	0.46	0.04
Min	0.00	10.45	-0.49	1.04	0.83	0.00	0.00	12.25	6.62	0.00	-0.18
Max	9.21	17.84	0.21	14.07	9.39	0.45	0.50	16.25	13.44	1.00	0.17
						Local SOEs					
Mean	1.92	13.73	0.03	2.57	1.64	0.03	0.14	14.47	9.91	0.38	0.07
SD	2.51	1.32	0.06	1.97	1.22	0.04	0.11	1.04	1.35	0.49	0.05
Min	0.00	10.45	-0.49	1.04	0.83	0.00	0.00	12.25	6.62	0.00	-0.18
Max	9.21	17.84	0.21	14.07	9.39	0.45	0.50	16.25	13.44	1.00	0.17
						Central SOEs					
Mean	2.49	14.11	0.03	2.54	1.78	0.03	0.10	14.84	10.07	0.44	0.07
SD	2.87	1.62	0.05	1.69	1.19	0.04	0.10	1.18	1.45	0.50	0.06
Min	0.00	10.47	-0.49	1.04	0.83	0.00	0.00	12.25	6.62	0.00	-0.18
Max	9.21	17.84	0.21	14.07	9.39	0.45	0.50	16.25	13.44	1.00	0.17
						Total					
Mean	1.24	13.13	0.03	2.17	2.03	0.04	0.16	14.59	9.19	0.34	0.08
SD	2.30	1.35	0.09	1.62	1.41	0.07	0.12	1.05	1.30	0.47	0.05
Min	0.00	10.45	-0.49	1.04	0.83	0.00	0.00	12.25	6.62	0.00	-0.18
Max	9.21	17.84	0.21	14.07	9.39	0.45	0.50	16.25	13.44	1.00	0.17

Panel B. Average anti-poverty donation amount (in CNY) by firm type and year

	2016	2017	2018	2019	2020
POEs	780,130	1,539,250	1,473,242	1,647,167	1,589,560
Local SOEs	1,091,839	1,641,903	2,226,231	2,750,260	3,449,513
Central SOEs	2,461,987	2,947,262	4,463,190	6,832,860	7,585,837

Panel C. Ratio of firm-level anti-poverty donation to total assets, by firm type and year

	2016	2017	2018	2019	2020
POEs	113.3336	320.2962	213.8729	203.3850	150.8157
Local SOEs	87.0092	156.0148	268.2118	206.3367	278.4045
Central SOEs	38.3707	51.5606	92.7107	124.5868	152.1680

Note: Calculated as the firm-level anti-poverty donation amount divided by total assets (in millions).

Panel D. Ratio of firm-level anti-poverty donation to China's GDP, by firm type and year

	2016	2017	2018	2019	2020
POEs	0.010452	0.018500	0.016026	0.016697	0.015683
Local SOEs	0.014628	0.019734	0.024217	0.027879	0.034033
Central SOEs	0.032985	0.035422	0.048551	0.069263	0.074843

Note: Calculated as the firm-level anti-poverty donation amount divided by China's GDP (in millions).

Table 2. Main analysis: Different corporate anti-poverty actions

VARIABLES	Model 1 Full sample	Model 2 Full sample	Model 3 Low corporate tax revenue	Model 4 High corporate tax revenue	Model 5 Low fiscal income	Model 6 High fiscal income	Model 7 Low analyst following	Model 8 High analyst following	Model 9 Low analyst report	Model 10 High analyst report	Model 11 No presence in Beijing	Model 12 Presence in Beijing
Policy x Central SOE		0.799***	0.577**	0.951***	0.684***	0.950***	0.531**	0.913***	0.561**	0.895***	0.697**	1.102***
		(0.139)	(0.153)	(0.131)	(0.090)	(0.174)	(0.184)	(0.138)	(0.191)	(0.116)	(0.168)	(0.151)
Test of Coefficient Differences			*Diff = 0.374 (p<0.01)*		*Diff = 0.266 (p<0.05)*		*Diff = 0.383 (p<0.01)*		*Diff = 0.334 (p<0.01)*		*Diff = 0.405 (p<0.01)*	
Policy x Local SOE		0.351*	0.125	0.602**	0.176*	0.663**	0.213	0.496**	0.208	0.518**	0.292*	1.173***
		(0.130)	(0.095)	(0.145)	(0.072)	(0.172)	(0.121)	(0.175)	(0.128)	(0.125)	(0.116)	(0.099)
Test of Coefficient Differences			*Diff = 0.476 (p<0.01)*		*Diff = 0.486 (p<0.01)*		*Diff = 0.284 (p<0.01)*		*Diff = 0.309 (p<0.01)*		*Diff = 0.881 (p<0.01)*	
Policy	0.345*	0.186	0.263	0.138	0.197	0.144	0.191	0.148	0.170	0.176	0.205	0.036
	(0.139)	(0.122)	(0.174)	(0.084)	(0.145)	(0.081)	(0.135)	(0.080)	(0.127)	(0.093)	(0.121)	(0.110)
Central SOE	0.537**	0.201	-0.038	0.500**	-0.069	0.548**	0.252	0.067	0.248	0.088	0.045	0.478*
	(0.190)	(0.124)	(0.136)	(0.152)	(0.127)	(0.169)	(0.152)	(0.186)	(0.130)	(0.189)	(0.135)	(0.178)
Local SOE	0.215	0.065	0.154	0.009	0.138	-0.022	0.179	-0.091	0.163	-0.079	0.150	-0.792***
	(0.122)	(0.134)	(0.116)	(0.224)	(0.119)	(0.243)	(0.104)	(0.239)	(0.091)	(0.210)	(0.117)	(0.088)
Asset	0.533***	0.528***	0.554***	0.495***	0.538***	0.496***	0.353***	0.654***	0.342***	0.692***	0.500***	0.534***
	(0.059)	(0.059)	(0.089)	(0.058)	(0.075)	(0.071)	(0.069)	(0.083)	(0.064)	(0.079)	(0.063)	(0.041)
ROA	0.531**	0.570**	0.833	0.360	0.717	0.280	0.427	1.109	0.458	0.967	0.664*	0.374
	(0.185)	(0.185)	(0.423)	(0.324)	(0.483)	(0.398)	(0.285)	(0.607)	(0.292)	(0.575)	(0.243)	(0.500)
Leverage	-0.027	-0.024	-0.026	-0.009	-0.001	-0.018	-0.012	0.000	-0.008	-0.014	-0.021	-0.010
	(0.017)	(0.017)	(0.026)	(0.028)	(0.021)	(0.029)	(0.016)	(0.038)	(0.016)	(0.031)	(0.019)	(0.038)
Market to book ratio	0.049	0.049	0.056	0.046	0.063	0.041	0.024	0.013	0.022	0.011	0.032	0.120***
	(0.025)	(0.024)	(0.035)	(0.026)	(0.034)	(0.029)	(0.035)	(0.036)	(0.033)	(0.039)	(0.022)	(0.016)
Earnings volatility	-0.679	-0.517	-1.200	-0.159	-0.789	-0.466	-1.063	0.010	-1.070	-0.014	-0.574	-0.271
	(0.362)	(0.363)	(0.681)	(0.384)	(0.664)	(0.473)	(0.557)	(0.986)	(0.612)	(0.968)	(0.487)	(0.851)
Board gender	0.109	0.110	0.192	-0.048	-0.078	0.110	0.092	-0.011	0.034	0.104	0.113	0.665**
	(0.207)	(0.208)	(0.383)	(0.213)	(0.337)	(0.195)	(0.265)	(0.311)	(0.273)	(0.314)	(0.228)	(0.206)
Local government education expense	-0.152**	-0.148*	-0.227*	-0.077	-0.197*	0.016	-0.149*	-0.131	-0.145*	-0.149	-0.157**	0.012
	(0.054)	(0.054)	(0.093)	(0.051)	(0.080)	(0.095)	(0.056)	(0.075)	(0.061)	(0.082)	(0.054)	(0.342)
Surplus reserves	0.202***	0.206***	0.290***	0.142***	0.254**	0.138**	0.144**	0.235**	0.151**	0.215**	0.187**	0.350**
	(0.039)	(0.039)	(0.055)	(0.030)	(0.056)	(0.037)	(0.035)	(0.053)	(0.036)	(0.052)	(0.044)	(0.090)
Board interlock	0.138**	0.134*	0.208*	0.057	0.172*	0.080	0.113	0.109	0.118	0.096	0.135*	0.017
	(0.049)	(0.049)	(0.091)	(0.050)	(0.069)	(0.054)	(0.070)	(0.076)	(0.065)	(0.076)	(0.055)	(0.104)
Lagged GDPPC growth	1.254	1.199	0.842	1.945	0.698	2.085	0.595	1.551	0.506	1.741	1.174	0.811
	(1.162)	(1.107)	(1.000)	(1.457)	(0.967)	(1.529)	(1.186)	(0.996)	(1.132)	(1.011)	(1.192)	(0.770)
Constant	-5.837***	-5.803***	-5.550**	-6.127***	-5.594**	-7.522***	-2.923**	-8.038***	-2.883*	-8.111***	-5.111***	-9.879
	(0.968)	(0.959)	(1.557)	(0.937)	(1.491)	(1.337)	(1.016)	(1.304)	(1.123)	(1.356)	(0.955)	(5.215)
Observations	13,893	13,893	5,927	7,965	6,703	6,504	7,168	6,720	7,299	6,590	12,302	1,586
R-squared	0.303	0.307	0.294	0.331	0.310	0.349	0.247	0.353	0.249	0.352	0.280	0.564
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The sample includes Chinese listed firms from 2016–2020. The dependent variable is log (donation amount +1). The donation amount is the total value of donations (cash and in-kind) made to registered poverty. Central SOE equals one if the central government predominantly controls the firm; and zero otherwise. Local SOE equals one if the local government predominantly controls the firm; and zero otherwise. Policy equals to one for the years 2019 and 2020 (2019 is the year of the policy issuance) and zero otherwise. We drop the singleton observations. The *p*-values on the coefficient differences across sub-samples are reported for two key variables of interest, in the row *Test of Coefficient Differences*. All regressions include industry fixed effects and province fixed effects. Standard errors are two-way clustered by city and year. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Robustness checks: Different corporate anti-poverty actions

VARIABLES	Model 1 Full sample	Model 2 Full sample	Model 3 Low corporate tax revenue	Model 4 High corporate tax revenue	Model 5 Low fiscal income	Model 6 High fiscal income	Model 7 Low analyst following	Model 8 High analyst following	Model 9 Low analyst report	Model 10 High analyst report	Model 11 No presence in Beijing	Model 12 Presence in Beijing
Policy x Central SOE		0.726***	0.504**	0.884***	0.630***	0.877***	0.578**	0.795***	0.598**	0.777***	0.610**	1.054***
		(0.125)	(0.150)	(0.112)	(0.101)	(0.141)	(0.185)	(0.124)	(0.179)	(0.102)	(0.153)	(0.117)
Test of Coefficient Differences			*Diff = 0.380 (p< 0.01)*		*Diff = 0.247 (p< 0.05)*		*Diff = 0.216 (p< 0.05)*		*Diff = 0.179 (p< 0.1)*		*Diff = 0.444 (p< 0.01)*	
Policy x Local SOE		0.255*	0.054	0.477**	0.117	0.525**	0.197	0.323*	0.177	0.356**	0.207	0.888***
		(0.119)	(0.087)	(0.131)	(0.067)	(0.152)	(0.117)	(0.147)	(0.137)	(0.096)	(0.106)	(0.069)
Test of Coefficient Differences			*Diff = 0.424 (p< 0.01)*		*Diff = 0.408 (p< 0.01)*		*Diff = 0.126 (p< 0.1)*		*Diff = 0.179 (p< 0.05)*		*Diff = 0.681 (p< 0.01)*	
Policy	0.364*	0.232	0.311	0.184*	0.226	0.197*	0.236	0.209*	0.226	0.228*	0.246	0.088
	(0.133)	(0.115)	(0.186)	(0.072)	(0.147)	(0.073)	(0.135)	(0.091)	(0.130)	(0.101)	(0.117)	(0.082)
Central SOE	0.546*	0.241	0.015	0.498**	-0.062	0.550**	0.344	0.123	0.341*	0.148	0.108	0.635***
	(0.197)	(0.126)	(0.149)	(0.130)	(0.142)	(0.151)	(0.170)	(0.168)	(0.151)	(0.168)	(0.127)	(0.117)
Local SOE	0.308**	0.198	0.270*	0.165	0.210	0.138	0.267*	0.128	0.260*	0.136	0.250*	-0.389***
	(0.108)	(0.104)	(0.122)	(0.176)	(0.126)	(0.168)	(0.106)	(0.179)	(0.094)	(0.160)	(0.101)	(0.073)
Constant	1.060	1.062	2.884	-0.458	1.722	-1.869	2.777*	-0.512	2.707*	-0.319	1.373	-4.292
	(0.872)	(0.883)	(1.522)	(0.799)	(1.321)	(1.473)	(1.019)	(1.162)	(1.215)	(1.198)	(0.893)	(4.269)
Observations	13,893	13,893	5,927	7,965	6,703	6,504	7,168	6,720	7,299	6,590	12,302	1,586
R-squared	0.203	0.206	0.206	0.188	0.226	0.208	0.194	0.239	0.193	0.240	0.200	0.406
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The sample includes Chinese-listed firms from 2016 to 2020. The dependent variable is log ((donation amount measured in CNY /total asset measured in millions of CNY) +1). The donation amount is the total value of donations (cash and in-kind) to registered poverty. Central SOE equals one if the central government predominantly controls the firm; and zero otherwise. Local SOE equals one if the local government predominantly controls the firm; and zero otherwise. Policy equals to one for the years 2019 and 2020 (2019 is the year of the policy issuance) and zero otherwise. We include the set of firm- and location-level control variables as in Table 2, but we do not report the coefficients to save space. We drop the singleton observations. The *p*-values on the coefficient differences across sub-samples are reported for two key variables of interest, in the row *Test of Coefficient Differences*. All regressions include industry-fixed effects and province-fixed effects. Standard errors are two-way clustered by city and year. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Further analysis: Anti-poverty awards and award givers

VARIABLES	Model 1 DV: Log (number of anti-poverty awards+1)	Model 2 DV: Log (number of anti-poverty awards from the ***central government***+1)	Model 3 DV: Log (number of anti-poverty awards from ***local governments***+1)
Policy x Log (anti-poverty donation+1)	0.002	0.006**	0.002
	(0.003)	(0.002)	(0.002)
Policy	0.001	-0.001	0.002
	(0.004)	(0.001)	(0.002)
Log (anti-poverty donation+1)	0.030***	0.004***	0.017***
	(0.003)	(0.001)	(0.001)
Constant	-0.180**	-0.093**	-0.056
	(0.062)	(0.020)	(0.045)
Observations	13,893	13,893	13,893
R-squared	0.173	0.086	0.126
Control	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes

Note: The sample includes Chinese-listed firms from 2016 to 2020. DV = dependent variable. Anti-poverty donation is the total value of donations (cash and in-kind) made to registered poverty. Policy equals to one for the year 2019 and onward (2019 is the year of the policy issuance) and zero otherwise. We include the set of firm- and location-level control variables, as shown in Table 2, but we do not report the coefficients to save space. We drop the singleton observations. All regressions include industry-fixed effects and province-fixed effects. Standard errors are two-way clustered by city and year. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Further analysis: Does the Tax-Deduction Policy Make Talkers Walk the Talk?

VARIABLES		Model 1 CSR reporters	Model 2 Non-CSR reporters
Policy x Central SOE		0.498***	0.840**
		(0.085)	(0.191)
	Test of Coefficient Differences	*Diff = 0.341 (p<0.01)*	
Policy x Local SOE		0.222	0.268*
		(0.171)	(0.116)
	Test of Coefficient Differences	*Diff = 0.045 (p>0.1)*	
Policy		0.455*	0.171
		(0.204)	(0.092)
Central SOE		0.203	-0.046
		(0.184)	(0.128)
Local SOE		-0.411	0.356**
		(0.195)	(0.110)
Constant		-8.214**	-1.753*
		(2.261)	(0.821)
Observations		3,858	10,013
R-squared		0.362	0.220
Control		Yes	Yes
Industry FE		Yes	Yes
Province FE		Yes	Yes

Note: The sample includes Chinese-listed firms from 2016 to 2020. The dependent variable is log (donation amount +1). The donation amount is the total value of donations (cash and in-kind) made to registered poverty. Central SOE equals one if the central government predominantly controls the firm; and zero otherwise. Local SOE equals one if the local government predominantly controls the firm; and zero otherwise. Policy equals to one for the year 2019 and onward (2019 is the year of the policy issuance) and zero otherwise. We include the set of firm- and location-level control variables as in Table 2, but we do not report the coefficients to save space. We drop the singleton observations. The *p*-values on the coefficient differences across sub-samples are reported for the two key variables of interest, in the rows *Test of Coefficient Differences*. All regressions include industry-fixed effects and province-fixed effects. Standard errors are two-way clustered by city and year. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Further analysis: Actions Firms Take to Reduce Poverty

Panel A: Six sub-actions firms take

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VARIABLES	DV: Employment dummy	DV: Education dummy	DV: Health & environment dummy	DV: Industry development dummy	DV: Basic needs dummy	DV: Others dummy
Policy x Central SOE	0.054**	0.039**	0.037	0.065*	0.058**	0.083***
	(0.017)	(0.010)	(0.026)	(0.027)	(0.015)	(0.018)
Policy x Local SOE	0.023*	0.006	0.014	0.068**	0.011	0.064***
	(0.008)	(0.008)	(0.010)	(0.020)	(0.010)	(0.013)
Policy	0.003	0.012	0.004	0.019	0.033**	0.020
	(0.005)	(0.016)	(0.009)	(0.010)	(0.010)	(0.010)
Central SOE	0.052*	0.028	0.014	0.095**	0.075**	0.024
	(0.021)	(0.013)	(0.019)	(0.028)	(0.018)	(0.013)
Local SOE	0.035	0.011	0.012	0.083**	0.050**	0.022
	(0.020)	(0.017)	(0.017)	(0.024)	(0.018)	(0.018)
Constant	-0.358*	-0.588**	-0.507***	-0.580**	-0.221	-0.535***
	(0.145)	(0.148)	(0.102)	(0.138)	(0.170)	(0.113)
Observations	13,893	13,893	13,893	13,893	13,893	13,893
R-squared	0.155	0.172	0.137	0.237	0.148	0.175
Control	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Categorization of targeted measures

Broad areas	Sub-areas of anti-poverty actions
Government economic responsibility	Employment creation *(Providing job opportunities, re-locating poor people from inhospitable areas for better employment)*
	Education *(Improving education in impoverished areas)*
Government social responsibility	Health & Environment *(Developing eco-environment; improving healthcare infrastructures; reducing ecological damages to compensate for economic losses associated with environment issues; and providing eco-jobs)*
	Industry development *(Growing businesses that leverage local strengths, e.g., new e-commerce and tourism)*
Redistribution	Basic needs *(offering subsistence allowances for the poor unable to shake off poverty by their own efforts)*
	Others *(Anti-poverty actions, including but not limited to: Chinese New Year visiting and purchasing the poor's agricultural products)*

Panel C: Three broad areas to which firms donated

	Model 1	Model 2	Model 3
VARIABLES	DV: Government economic responsibility	DV: Government social responsibility	DV: Redistribution
Policy x Central SOE	0.075**	0.039**	0.083***
	(0.025)	(0.011)	(0.013)
Policy x Local SOE	0.075**	0.023**	0.044**
	(0.020)	(0.008)	(0.016)
Policy	0.021	0.013	0.041*
	(0.012)	(0.018)	(0.015)
Central SOE	0.097**	0.026	0.074**
	(0.028)	(0.015)	(0.023)
Local SOE	0.079**	0.017	0.054*
	(0.023)	(0.018)	(0.021)
Constant	-0.524**	-0.604**	-0.465**
	(0.152)	(0.148)	(0.153)
Observations	13,893	13,893	13,893
R-squared	0.239	0.186	0.210
Control	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes

Note: For both Panels A and C, the sample includes Chinese-listed firms from 2016 to 2020. The dependent variable is the dummy variable corresponding to each measure which the firm has taken to donate and reduce poverty. Central SOE equals one if the central government predominantly controls the firm; and zero otherwise. Local SOE equals one if the local government predominantly controls the firm; and zero otherwise. Policy equals one for the year 2019 and onward (2019 is the year of the policy issuance) and zero otherwise. We include the set of firm- and location-level control variables as in Table 2, but we do not report the coefficients to save space. We drop the singleton observations. All regressions include industry-fixed effects and province-fixed effects. Standard errors are two-way clustered by city and year. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Further analysis: The effect of corporate anti-poverty donations on the society

Panel A. Aggregate effect of corporate anti-poverty donations on the society (province-level)

VARIABLES	Model 1	Model 2	Model 3	Model 4
Corporate donation				
Policy x Log(corporate anti-poverty donation/ poverty $_{t-1}$)	-0.043	-0.058	-0.046	-0.061
	(0.033)	(0.031)	(0.034)	(0.033)
Log(corporate anti-poverty donation/poverty $_{t-1}$)	0.055*	0.104***	0.053*	0.059**
	(0.021)	(0.017)	(0.020)	(0.017)
Policy	0.392*	0.611**	0.418*	0.552**
	(0.137)	(0.147)	(0.140)	(0.152)
Government expenditure				
Log(Local government expenditure on agriculture/ poverty $_{t-1}$)	-0.082		-0.099	
	(0.161)		(0.191)	
Log(Local government expenditure on health/ poverty $_{t-1}$)	0.208		0.151	
	(0.250)		(0.327)	
Log(Local government expenditure on Urban-Rural development/ poverty $_{t-1}$)	0.083		0.084	
	(0.075)		(0.076)	
Log(Local government expenditure on social security and employment/ poverty $_{t-1}$)	0.116		0.095*	
	(0.071)		(0.035)	
Log(Local government expenditure on education/ poverty $_{t-1}$)	-0.311		-0.270	
	(0.512)		(0.582)	
Log(Local government expenditure on R&D/ poverty $_{t-1}$)	0.083		0.081	
	(0.129)		(0.130)	
Log(Central fund to reduce poverty/ poverty $_{t-1}$)	0.088		0.090	
	(0.087)		(0.086)	
Government revenue				
Log(Corporate tax payable/ poverty $_{t-1}$)	-0.044			0.124*
	(0.134)			(0.040)
Economic opportunities for poverty				
Growth in GDP per capita $_{t-1}$	-0.337	0.118	-0.260	0.938
	(2.123)	(0.623)	(1.918)	(0.561)
Constant	-0.828	-0.076	-0.649	-0.998**
	(2.454)	(0.049)	(2.232)	(0.291)
Observations	97	97	97	97
R-squared	0.832	0.794	0.831	0.816
Province FE	Yes	Yes	Yes	Yes

Note: The sample includes 31 provinces in China from 2016–2019. We exclude the year 2020 because the poverty population data in 2020 is not reliable. The dependent variable is the poverty population reduction (in percentage terms). Policy equals to one for the year 2019, and zero otherwise. Corporate anti-poverty donation is defined as the aggregated value of corporate donations (cash and in-kind) made to registered poverty, at the province-year level. All regressions include province fixed effects. We drop the singleton observations. Standard errors are two-way clustered by province and year. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Panel B. Aggregate effect of corporate anti-poverty donations on the society (city-level)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
VARIABLES	Full sample				Cities with listed firms				Cities without listed firms	
Corporate donation										
Policy x Log(corporate anti-poverty donation/ population $_{t-1}$)	-0.041	-0.040	-0.040	-0.041	-0.034	-0.040	-0.034	-0.038		
	(0.027)	(0.023)	(0.027)	(0.024)	(0.043)	(0.022)	(0.029)	(0.019)		
Log(corporate anti-poverty donation/ population $_{t-1}$)	0.051***	0.056**	0.056**	0.051***	0.037*	0.051**	0.038	0.043***		
	(0.009)	(0.018)	(0.014)	(0.008)	(0.014)	(0.016)	(0.020)	(0.007)		
Policy	0.731***	0.732***	0.730***	0.733***	0.710***	0.731***	0.709***	0.731***	0.738**	0.739***
	(0.090)	(0.091)	(0.090)	(0.089)	(0.111)	(0.100)	(0.107)	(0.100)	(0.177)	(0.082)
Government expenditure										
Log(local government expenditure on education/ population $_{t-1}$)	0.020		0.016		0.099***		0.099**		0.056***	
	(0.041)		(0.040)		(0.014)		(0.026)		(0.010)	
Log(local government expenditure on R&D / population $_{t-1}$)	-0.004		-0.001		0.023		0.024		-0.050	
	(0.020)		(0.025)		(0.021)		(0.024)		(0.030)	
Government revenue										
Log(Corporate tax payable/ population $_{t-1}$)	0.004			0.003	0.001			0.008		
	(0.008)			(0.008)	(0.025)			(0.016)		
Economic opportunities for poverty										
Growth in GDP per capita $_{t-1}$	1.446**	1.448**	1.445**	1.450**	1.737	1.701*	1.736*	1.717*	1.162	1.163*
	(0.505)	(0.488)	(0.505)	(0.491)	(0.914)	(0.708)	(0.709)	(0.707)	(0.955)	(0.476)
Constant	-0.071	0.066	-0.047	0.060	-0.761***	0.056	-0.764**	0.033	-0.148	0.075
	(0.352)	(0.075)	(0.347)	(0.064)	(0.134)	(0.094)	(0.228)	(0.076)	(0.140)	(0.067)
Observations	339	339	339	339	230	230	230	230	109	109
R-squared	0.576	0.575	0.575	0.575	0.520	0.515	0.520	0.516	0.755	0.753
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The sample includes 166 cities, where the designated poor counties are located, in China from 2016 to 2020. We drop city-year observations with missing key fiscal expenditure indicators, with missing values for lagged populations, and with missing information on GDP per capital. The dependent variable is the designated poverty county reduction (in percentage terms). Corporate anti-poverty donation is defined as the aggregated value of corporate donations (cash and in-kind) made to registered poverty, at the city-year level. Policy equals to one for the years 2019 and 2020 (2019 is the year of the policy issuance) and zero otherwise. All regressions include province-fixed effects. We drop the singleton observations. Standard errors are two-way clustered by province and year. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.