BALANCING ACT IN CHINA: MANAGING POLICY OVERCOMPLIANCE WITH GOAL CONFLICT

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Abstract

While previous research on policy implementation has primarily focused on the constraints imposed by formal and informal rules and structures, this study highlights the additional role played by the externalities arising from multiple goals in constraining policy implementations. The pursuit of each goal at all costs is constrained by conflicting goals with comparable importance, leading to the emergence of balanced efforts when over-compliance may be socially undesirable. Using event studies and a staggered difference-in-differences design on original datasets of daily intra-city mobility during China's 2020 COVID-19 epidemic, and leveraging a natural experiment of a poverty elimination campaign, the empirical analyses find that cities that need to balance poverty elimination and pandemic control succeeded in both goals, despite a reduction of 40 percent in the severity of their COVID-19 lockdown measures, compared to a counterfactual scenario where poverty alleviation evaluation was not a factor.

Keywords: policy implementation, bureaucracy, central-local relations, China.

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1 Introduction

Research on policy implementation extensively explores the design of regulations, hierarchies, procedures, and incentive structures to effectively control agent behavior and achieve desired outcomes. Formal rules and processes have received considerable attention in this regard (McCubbins and Schwartz 1984; Wilson 1989; Miller 2005). Recent studies have both positive effects of these rules and structures, such as mitigating information withholding (Jia and Nie 2017) and incentivizing efforts (Lü and Landry 2014). Furthermore, the role of informal institutions, in shaping bureaucratic behaviors has also garnered significant attention. For example, studies have examined how patronage networks (Jiang 2018), campaigns (Looney 2015), and anti-corruption drives (Zhan and Zhu 2022 incentivize efforts across policy areas.

Bureaucrats are constrained by a series of written and unwritten rules in the implicit contract with the principal. However, in many instances, agents may have multiple principals or a single principal assigning them multiple tasks, resulting in their adherence to multiple contracts. In such contexts, the behaviors of agents are not solely shaped by the rules prescribed within each individual contract in isolation but are also influenced by the interdependencies and externalities that arise from enforcing these contracts and pursuing goals in them. This paper brings attention to this often overlooked interdependency and focuses on the interplay of multiple goals in the context of policy implementation. This paper argues that the relative weight assigned to each goal can play a crucial role, alongside formal and informal rules, in policy implementation, by directly influencing agents' calculations of trade-offs.

The interplay of different goals and multitasking in general are often studied in the context of potential pitfalls because the principal-agent literature has traditionally focused on addressing the problem of lack of compliance, which introduces various challenges in multitasking scenarios (Holmstrom and Milgrom 1991; Dewatripont and Tirole 1999; Dewatripont, Jewitt, and Tirole 1999; Bolton and Dewatripont 2004; Rasul and Rogger 2018). However, it is essential to recognize that there can be normative reasons to consider excessive zeal in pursuing a specific goal as problematic, leading to the issue of overcompliance. From both a social and principal's perspective, complete compliance may not always be desirable. The adverse outcomes of overcompliance are particularly evident in authoritarian states where upward accountability is rigid, and external constraints are lacking, as exemplified by historical events such as the over-collection of grains during the Great Leap Forward (Liu and Zhou 2021) and excessive repression during Stalin's Great Terror (Zhukov and Talibova 2018).

This perspective raises a different question from the classical focus on improving agent incentives in policy implementation: how to make agents balance their efforts. I argue that under certain scope conditions, conflicting goals can impose trade-off constraints on agents, prompting them to internalize the costs associated with excessively pursuing one goal at the expense of the other. By reorienting the objective function of delegation, multitasking can be evaluated from the new perspective of policy implementation and constraining overcompliance.

Contemporary China provides a compelling case for studying the dynamics of multitasking and policy implementation. The country's strong state delegates multiple conflicting tasks to generalist local officials and is susceptible to issues of overcompliance due to its top-down governance system. Furthermore, Chinese local officials are entrusted with a diverse range of goals that can inherently clash with one another: e.g. promoting social welfare (Hammond 2013; Zuo 2015), maintaining social stability (Bulman 2016), fostering economic development (Li and Zhou 2005; Jia, Kudamatsu, and Seim 2015; Landry, Lü, and Duan 2018), extracting fiscal resources (Lü and Landry 2014), reducing poverty (Donaldson 2007), and ensuring environmental protection (Chen, Li, and Lu 2018). The COVID-19 pandemic offers a distinctive opportunity to conduct a quantitative examination of this question by imposing a universal objective of maintaining zero COVID-19 infections into the existing multitasking responsibilities of all local officials.

The COVID-19 pandemic became a pervasive threat to the political survival of local officials in China, who then pursued extreme pandemic control measures to secure their careers such that they are prone to single-minded over-compliance. These actions, while aligned with their public health goal, incurred substantial socio-economic costs, affecting rural communities (Huan Wang et al. 2021), the urban economy (You et al. 2020), the national economy (Jin et al. 2021), and global trade (Verschuur, Koks, and Hall 2021). They also indirectly led to non-COVID related deaths, as evidenced by a high ratio of excess mortality to reported COVID-19 mortality in China's provinces outside Hubei (Haidong Wang et al. 2022).

To investigate how conflicting goals can mitigate the tendency of local officials to implement excessive lockdowns during COVID-19 outbreaks, I employs event study and staggered Difference-in-Differences methods on a novel dataset, recording daily intra-city mobility, COVID-19 cases, and economic factors across 317 Chinese cities from January 21 to April 28, 2020, along with data from an original poverty alleviation dataset. I leverage the timing of a significant poverty elimination campaign endorsed by General Secretary Xi Jinping to manipulate the existence of conflicting goals against pandemic control. I find compelling evidence supporting the hypothesis that officials tasked with poverty elimination exhibit less stringent lockdown measures during outbreaks. Additionally, these officials demonstrate a quicker reopening of their cities after achieving zero COVID-19 cases. Importantly, once the poverty elimination target is met, these officials subsequently impose stricter lockdown measures, indicating a clear moderation effect of poverty targets on their pandemic response.

Remarkably, these officials successfully suppressed or contained the outbreaks while simultaneously pursuing their poverty elimination goals. The presence of conflicting goals related to poverty elimination leads to a 40 percent reduction in the severity of COVID-19 lockdowns in cities under poverty elimination target, compared to a counterfactual scenario where poverty alleviation evaluation was not a factor. I also find evidence that richer cities without poverty elimination targets systematically lockdown more and reopen slower than cities under such targets, even after controlling their respective economic development level and economic structure.

Theory

When are Conflicting Goals Constructive?

Multitasking and setting conflicting goals have plenty of critics. The principal-agent literature generally favors single-task assignment over multitasking because single-tasking agents can be given greater autonomy to work within budgets without worrying about trade-offs between multiple tasks (Holmstrom and Milgrom 1991; Dewatripont and Tirole 1999). By contrast, multitasking agents need to be more closely monitored to avoid displacement of budgets in pursuing the more observable task (Dewatripont, Jewitt, and Tirole 1999; Rasul and Rogger 2015). The literature treats single-tasking as the optimal solution because it mainly focuses on increasing agents' effort.

Government agencies are inherently multitasking agents and constantly face a diverse set of tasks such that public administration as a discipline treat multitasking agents as the necessary evil (Miller 2005). Wilson (1989) argues that the principal needs to define a "core mission" for the agent and other tasks need to be coherent parts of it. "A good executive realizes that workers can make subtle, precise, and realistic judgments, but only if those judgments refer to a related, coherent set of behaviors. People cannot easily keep in mind many quite different things or strike reasonable balances among competing tasks. People want to know what is expected of them; they do not want to be told, in answer to this question, that "on the one hand this, but on the other hand that."" (p.371)[1] After all, if one task is detrimental to the other, i.e. incurs negative externalities, then spending resources on both will cancel each other out. Instead of motivating the agent to try harder to perform both tasks, conflicting tasks will induce unbalanced efforts (Dewatripont and Tirole 1999; Bolton and Dewatripont 2004).

Therefore, both political science and economics literature treat conflicting goals as suboptimal delegation when they consider monitoring costs, clarity of incentives, and unambiguous performance

[1] Party mouthpiece has described Xi Jinping's governance as having a dual nature of "on one hand this, but on the other hand that."(品读习近平的"三个既要又要" https://web.archive.org/web/20230202034602/http://cpc.people.com.cn/n/2015/1117/c241220-27824908.html)

evaluation. However, these objective may not be the only ones that matter in delegation or policy implementation. I argue that conflicting goals have important but understudied advantages when overcompliance is the problem. There can be normative reasons to consider excessive zeal in pursuing a specific goal as costly and dangerous for a society due to unintended consequences. Indeed, if there exists uncertainty about the consequences of full compliance, it is rational for the principal to set feasible conflicting goals for agents to balance efforts and avoid extremes.

Suppose a principal delegates a goal to their bureaucrats and set budgetary and institutional constraints. Given the goal, the agent can devise his own policies and calibrate implementation. However, the otherwise conducive strong incentives and observable results can lead to overcompliance of some zealot agents. Wilson (1989) call this tendency “mission madness” which is usually seen in intelligence and covert-action agencies (p.370). It is not coincidental that overcompliance is observed in secretive agencies that are shielded from democratic oversight and accountability. Agents have incentives to break rules when their performance depends only on the success of the goal. The same problem is especially acute under authoritarianism when government agents’ power has even fewer constraints. Not only is budgetary constraint rarely binding, authoritarian agents can also use coercion and breach citizens’ rights to achieve mandated goals and leave the principal to bear the loss of legitimacy.

Building formal policy implementation measures, such as strengthening institutions or implementing budgetary constraints, can be a time-consuming and politically challenging process. Alternatively, conflicting goals can serve as an impromptu mechanism to compel agents to internalize the costs associated with overly pursuing one goal at the expense of another. These conflicting goals disrupt the otherwise linear relationship between inputs and outputs in single-tasking scenarios. Increasing efforts towards one goal comes at the expense of the other, imposing constraints on agents’ maximization problem and holding them accountable for the resulting costs. Agents are required to strike a balance between pursuing multiple objectives rather than solely maximizing a single objective and externalizing the associated costs. For instance, if reducing government debt becomes an additional goal alongside promoting economic growth for local officials, they would need to identify more profitable projects that can foster economic growth while simultaneously minimizing debt.

Not all conflicting goals result in these advantages. There are certain conditions under which the conflict can be meaningfully constructive. These conditions include:

1. Comparable Importance: The conflicting goals must hold comparable importance, meaning that sacrificing one goal for the sake of another would result in a real loss for the agent. If the agent can still achieve a significantly higher reward by single-mindedly focusing on the prioritized goal, the punishment for failing to achieve the other goal may be overshadowed, leading to an imbalanced allocation of resources. Appendix A.1 provides a formalization of such a case that induces balanced efforts.

2. Feasibility of Balanced Efforts: It is crucial that the agent has a feasible way to allocate efforts and resources between the conflicting goals while achieving satisfactory performance in both. If there is no practical approach for the agent to successfully accomplish both goals, the presence of conflicting goals may lead to frustration and an eventual surrender to the failure of delivering all goals or data falsification.

Political Incentives and Conflicting Goals in China

Political incentives has always been an important part of governance for the People' s Republic of China since its founding. As early as the first Five-Year Plan (1953–1958), the party center set specific production targets for various goods, from steel to sugar, and delegated the authority and responsibility for their accomplishment to local governments.[2] In a central planning regime, these targets can be imperative and carry high-powered incentives. The results of one-sided incentives can be catastrophic. Studies of the Great Leap Forward movement show that career incentives led to overzealous enforcement of procurement and overly ambitious grain yield targets caused increased famine fatalities (Liu and Zhou 2021).

The legacy of top-down targets persisted after the 1978 market reform. The annual meeting of

[2]Report of the first Five-Year Plan for the national economic development of the PRC. https://web.archive.org/web/20230202034902/http://www.gov.cn/test/2008-03/06/content_910770.htm

the National People' s Congress in March continues to set socioeconomic goals for the following year, and the provincial people' s congresses meet before that to set local goals. Although these goals are no longer as binding as they were in the planned economy, the setting of goals after the reform is supported by the Communist Party' s personnel management system, in which the upper-level Party committee has the power to transfer, appoint, promote, and dismiss lower-level officials (Manion 1985). Superiors wage campaigns and set higher targets for their preferred policy outcomes to convey their weights in performance evaluations (Li et al. 2019). Meanwhile, local inputs are suppressed in these campaigns (Looney 2015) and implementation are skewed by political priorities (O' Brien and Li 2017). One example of such integration of socio-economic targets into China' s top-down incentive structure is the highly motivated bureaucracy to promote economic growth (Li and Zhou 2005; Jia, Kudamatsu, and Seim 2015; Landry, Lü, and Duan 2018; Jiang 2018) and fiscal extraction (Lü and Landry 2014).

After Xi Jinping took power in 2012, political incentives became more intense due to crackdowns and centralization of power. Officials are now held accountable with harsher sanctions for failing to meet targets. The stakes for underperforming have risen (Tu and Gong 2022), with dismissals and demotions becoming a common outcome. In Xi's first term, 11 percent of prefectural party secretaries faced dismissal or demotion (Li and Manion 2022), compared to only 2 percent from 1998 to 2007 (Landry, Lü, and Duan 2018). In 2020, the largest category of sanctioned officials, numbering 50,527 out of 119,224, were punished for "lazy governance" (懒政).[3] The high pressure to succeed leads to a risk of officials taking tasks to extreme measures to protect themselves.

How do the agents judge the relative importance of different priorities? Admittedly the party center in Beijing is not transparent about the precise weights, and local agents need to parse through state media or leader's speeches to decipher upper-level signals. However, despite the paradoxical signals from the center, local insiders can usually correctly grasp the priorities (Huang 2013). Even the formal evaluation rules are circulated and become open secrets (Zuo 2015). Therefore, both subjectively and objectively, local agents have judgements of which priorities are comparable or

[3]Central Commission for Disciplinary Inspection, January 26, 2021, www.ccdi.gov.cn/toutiao/202101/t20210126_234809.html.

asymmetric. The real question is an empirical one: how do outside observers, lacking inside information and political acumen, judge the relative importance of goals? This paper operationalizes the problem by choosing two goals that are publicly and repeatedly backed by threats of severe punishment: zero tolerance of COVID-19 infections and poverty elimination.

However, constructive conflicting goals are limited to be about political survival or crisis management. Indeed, such policy conflict has already been used in everyday governance in China and yield positive results. One notable example would be the delicate balance between environmental protection and economic growth. Single-minded pursuit of either through bureaucratic push would lead to significant socio-economic costs. Since the inclusion of environmental indicators in civil servants' performance evaluations in 2006, there has been an increasing emphasis among local officials on reducing pollution, even if it comes at the cost of sacrificing economic growth (Chen, Li, and Lu 2018). Researches show local officials have managed to navigate this conflict by exploring alternative approaches that promote economic development while simultaneously minimizing environmental harm (Du and Yi 2021; Zhang 2021; Sun et al. 2023).

China' s Localized Lockdown

China' s local governments have always been responsible for a variety of tasks, but rarely have they been uniformly subjected to one task with such clarity: the elimination of COVID-19. The party center prioritized pandemic control as "the biggest political mission" in a document dated January 30, 2020.[4] However, China never imposed a national lockdown, much like its lack of a national ban on live poultry sales (Van Den Dool 2023), to incorporate the multifaceted interests. The party center opted for a decentralized approach, leaving means of pandemic control to local discretion but holding local officials accountable for results. Each city designs its own strategy of pandemic control and implements localized lockdown.

The variations in pandemic control measures and their enforcement have been highly noticeable,

[4] "关于做好新型冠状病毒感染肺炎疫情防控和脱贫攻坚有关工作的通知," State Council Poverty Alleviation Office, January 30, 2020.

leading citizens to designate certain localities as models for effective management. For instance, some cities in Henan province received widespread praise from millions of citizens online for their prompt and stringent measures to block traffic from Wuhan as early as the end of December 2019[5].

Common measures employed to enforce lockdowns in China include: 1. Closure of street stores. 2. Extension of breaks for schools. 3. Suspension of public transportation. 4. Restriction of neighborhood entry and exit. 5. Closed-loop management of factory production. 6. Restriction on college students leaving campuses. 7. Cancellations of public gatherings.

However, the strictest measures enforced during the lockdown involved complete confinement within residences, where individuals were not permitted to leave their apartments without permission. In such cases, people relied solely on their existing food stocks or deliveries for sustenance. Noncompliance with these measures was met with coercive enforcement by community COVID workers, commonly referred to as "big white," (大白) or by the police in the name of Infectious Diseases Law.[6]

Chinese local officials had few constraints in their lockdown decisions in 2020. First, local officials had administrative autonomy: they were granted such unprecedented power in the name of pandemic control that they could lock down cities with millions of people even with a single infection. Moreover, they had a soft fiscal budget to weather economic shocks brought by the lockdowns. The central government approved local governments to issue 3.75 trillion RMB in special bonds (74 percent more than 2019' s debt ceiling) and 1 trillion RMB in pandemic special bonds.[7]

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[5]Weibo. s.weibo.com/weibo?q=%23来抄河南的作业%23

[6]Law of the PRC on Prevention and Treatment of Infectious Diseases 2013, Chapter 1, Article 12: "All units and individuals within the territory of the PRC must accept investigations, inspections, sample collections, isolation treatments and other prevention and control measures related to infectious diseases by disease prevention and control institutions and medical institutions, and provide accurate information about the relevant circumstances."

[7] "2020 年上半年中国财政政策执行情况报告," Ministry of Finance, August 6, 2020, www.gov.cn/xinwen/2020-08/06/content_5532865.htm

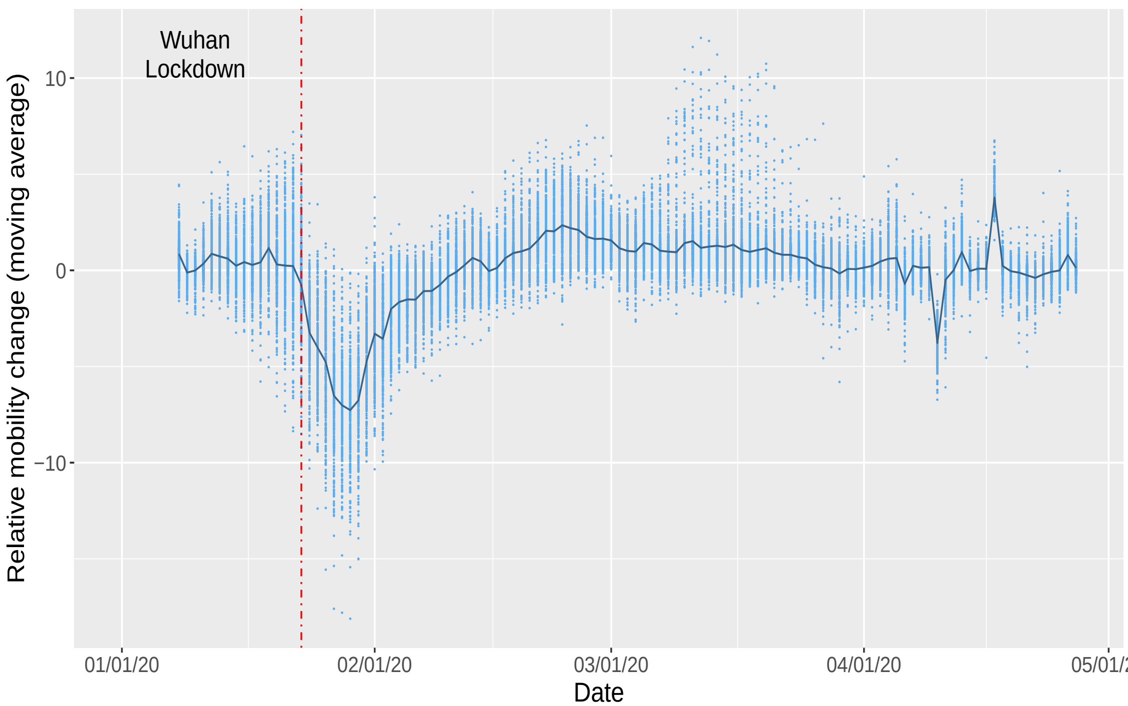

Figure 1: Mobility change of China' s cities from January to April 2020

Figure 1 reflects the localized lockdown. Based on data I collected, it shows the seven-day moving average of intra-city mobility changes in China' s cities. The horizontal axis captures each day from January 8, 2020, to April 28, 2020 (first week is used as baseline). Each point represents a city. Points below zero represent cities that decrease mobility, i.e., impose more lockdowns, compared to the day before. Points above zero represent cities that increase mobility, i.e., relax lockdown, compared to the day before. The dark blue line captures the national mean. Most cities imposed lockdowns in late January and began to reopen in mid-February. By observing the spread of points on each day, we can see the significant variation across cities in China.

Localized response is institutionalized in the Emergency Response Law, which requires that county-and-above governments[8] take action to immediately contain the emergency and then report to higher level governments, bypassing the immediately higher level of leadership if necessary. This

[8]In China as of 2020, there are 2844 counties embedded within 333 prefectural cities and 4 municipal cities. These 333 prefectural cities fall under the jurisdiction of 27 provinces. The 4 municipal cities, on the other hand, are at the provincial level, leading to a total of 31 provincial administrative regions in China.

means local governments are granted on-the-spot discretion during crises and only ex-post upward reporting is required.

Lockdown enforcement is an excellent choice for comparisons among local decision-making for three reasons: salience, attributability, and measurability.

First, the political outcome of the lockdown is of great importance to local decision makers. Every city leader had to weigh this political decision because the pandemic could hit the city just as it devastated Wuhan. Failure to control the pandemic outbreak could result in immediate dismissal or suspension, while a prolonged lockdown could lead to widespread unemployment. Therefore, the lockdown decisions are made after careful consideration, which should reflect a leader' s calculated decision making.

Second, human mobility is more attributable to political will to implement than other policy outcomes, such as economic development. Like any policy outcome, human mobility is due to three factors: political will, implementation capacity, and subject compliance. Lockdown is a much easier task to implement than the more complex tasks of creating economic growth or building "clean" governance, where mechanisms from inputs to outputs are not straightforward. Moreover, compliance to pandemic control measures during the early outbreak in 2020 was high because the preferences of the public and the government on this issue were largely aligned. Therefore, local mobility would track more closely with local implementation of lockdown.

Third, the outcome of the policy decision is very transparent: the mass mobility of people can be tracked with modern technology and is difficult to manipulate. This also allows identifiable comparisons between different places. Mobility-restricting measures ranged from month-long city-wide lockdowns to targeted quarantines of specific buildings and were often communicated through local media or even area-coded text messages. Due to the opacity of regulations and complexity of enforcement, mobility data is more accurate than formal announcements to measure local lockdowns.

With decentralized decision making, we see various pandemic control approaches, from different localities down to villages. The mandated local discretion seems paradoxical, as the local agents in Wuhan were the ones who covered up the emergence of the infectious disease and did not report it in the first place. However, allowing local discretion turns out to be an effective solution to pandemic control. Just as the congressional control literature observes (Weingast and Moran 1983; McCubbins and Schwartz 1984), monitoring results alone enabled the party to induce a nationwide pandemic control response. If they could observe policy outcomes and punish lapses, they did not need to monitor action.

Research Design and Hypotheses

Examining how officials respond to conflicting goals requires manipulating the goals and examining the changes in their decision making. It is nearly impossible for a researcher to assign goals to government officials. However, in the early days of the COVID-19 pandemic, China provides a natural experiment in which local officials were granted autonomy in their lockdown decisions and faced different priorities temporally and geographically. The configuration of the city-day decision-making data structure provides an ideal setting to analyze the research question at hand.

The Conflicting Goal: Poverty Elimination

While most officials were bound to the single task of zero-COVID, one group of officials had another policy mission of paramount importance: eliminating poverty in their jurisdictions by the end of 2020. The equal importance of poverty elimination and pandemic control was manifest in the constant juxtaposition of the two in Xi Jinping's speeches[9] and State Council's directive to resume poverty reduction evaluation when COVID case number had not yet peaked.[10] In other words, some officials had equal priorities until they achieved poverty elimination. The main metric for a county to no longer be designated poor is a poverty incidence rate below 2 percent (3 percent

[9] *Xinhua*, March 6, 2020, http://www.xinhuanet.com/politics/2020-03/06/c_1125674559.htm

[10] "扶贫系统积极妥善部署疫情防控和脱贫攻坚工作," State Council Poverty Alleviation Office. Feb 6, 2020.

for the Western region).[11] In retrospective inspections, the error rate of exiting poor households needs to be lower than 2 percent. Identification of the poverty incidence rate is based on a national anti-poverty campaign in 2014 that documented 89.2 million individuals living in poverty.

When Xi Jinping's poverty elimination campaign began in 2015, government officials at all levels signed a contract with their superiors promising to eradicate poverty in a timely manner. To hold county leaders accountable, the central government mandated that county party secretaries and government heads stay in their positions until poverty was eliminated, with the phrase "no transfer until elimination" used to emphasize this.[12] As Guizhou's provincial secretary Sun Zhigang put it, "The General Secretary [Xi Jinping] said, 'you have signed a military pledge. There is no joking in the military. If you have not accomplished it [poverty elimination], bring me your head."[13] This strong language indicates that leaders at all levels were under great pressure from the top. Specifically, city leaders were responsible for coordinating, policymaking, supervising, and reviewing poverty elimination efforts in their jurisdiction to ensure that poor counties met the poverty elimination deadline. Poverty elimination was effectively a political necessity for city leaders until the pandemic hit.

The procedures to opt out of being classified as a poor county consists all three levels of government: county, prefecture, and province. The poor county government applies for the exit. Then, the prefectural government conducts a preliminary examination of the progress and then applies for provincial approval if it deems the poverty target completed. The provincial government then sends down inspection teams to the county and the provincial leadership decides whether to approve the application. In addition, the State Council also randomly selects poor counties to inspect progress, as it did in 2019 for 60 of the 283 poor counties that graduated in 2018. The inspection was conducted in undercover by selected third-party personnel from ten universities and

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[11] "贫困县退出专项评估检查实施办法（试行）," State Council Poverty Alleviation Office, September 30, 2017.

[12] "脱贫攻坚责任制实施办法," General Office of the Chinese Communist Party, October 17, 2016.

[13] Official documentary "Up and Out of Poverty" (摆脱贫困). web.archive.org/web/20230202040030/https://www.bjd.com.cn/yaowen/2021/02/21/50549t191.html

institutes.[14] In previous inspections, the State Council found hundreds of households that were incorrectly exited from poverty designation and pressured for improvements.

Due to the pressing deadline in 2020 and pandemic-related mobility restrictions, poverty eradication efforts were impacted. Many poverty alleviation measures, such as allowing non-farm wage labor to travel to cities and relocating isolated households to places with jobs (异地搬迁脱贫), rely on labor mobility. The State Council estimated that two-thirds of poor households earn two-thirds of their income from being migrant laborers.[15] As a result, local governments placed special emphasis on allowing workers to resume movement. For instance, poor cities in Guangxi province organized 13560 workers to return to Guangdong's factories, with 35 percent being from documented poor households, in February 2020.[16] Apart from these, resuming production in local industries (特色产业脱贫), such as food processing and farming, and enabling the mobility of products to outside markets were also important in keeping poor households employed.[17]

In addition to resuming work opportunities for poor households, the poverty elimination campaign in China involves direct fiscal subsidies, such as agricultural subsidies, compensation for relocation, the ability to join cooperatives, easier access to microfinance, and higher reimbursement rates for medical treatment (Zuo, Wang, and Zeng 2021, 7). Poor cities rely heavily on fiscal transfers from higher levels of government, but those funds are specifically designated for poverty reduction, making tax revenues from other economic sectors crucial for the local governments' day-to-day operations. Extended closures can, therefore, present a challenge to the government's basic functioning.

[14] National Rural Revitalization Administration, web.archive.org/web/20230202040540/http://nrra.gov.cn/art/2019/7/2/art_2241_381.html

[15] "国务院联防联控机制权威发布," April 1 2020, web.archive.org/web/20230202041545/http://www.gov.cn/xinwen/gwylflkjz77/wzsl.htm

[16] National Rural Revitalization Administration, web.archive.org/web/20230202040616/http://nrra.gov.cn/art/2020/2/25/art_5_112887.html

[17] *The Paper*, April 19 2020, web.archive.org/web/20230202040821/https://m.thepaper.cn/newsDetail_forward_7044993

Eliminating poverty is a sustained effort as households can easily fall back into poverty once their income stops. According to Luo et al. (2020), 23 percent of households lifted from poverty feared falling back due to COVID-19 in early 2020. Hence, local governments must not only reduce existing poverty but also prevent new poverty from emerging during the pandemic. Until the provincial inspections are complete, both county and supervising prefectural governments must maintain the progress made in poverty elimination.

Achieving Poverty Elimination

Poverty reduction is operationalized in such a way that all counties officially designated as poor in their jurisdictions "graduate" from the designation. As of January 21, 2020, 106 of China' s 337 cities (333 prefectures + 4 municipalities) still had poor counties in their jurisdictions ("poor cities"), as shown in Figure 2.[18] Darker blue means the city has at least one designated poor county. 100 of them are outside Hubei Province.

The last of the procedures to opt out of being classified as a poor county is a public notification period of seven days. During this period, citizens may object to the approval of the designation. The public notification means that the provincial government is willing to approve the exit of these counties from the poverty designation and is confident in communicating its intention to the public. Given upward accountability and lack of downward accountability, I treat the date of the public announcement as the time when city leaders were sure that the approval by their respective superiors would be prompt.

From January 21 to April 28, 2020, provincial governments approved 65 of the 100 poor cities outside Hubei for the claim of poverty elimination (progress plotted in Figure 3).

Identifying the Effects of Conflicting Goals

Given the competing and equally prioritized goals of achieving zero COVID cases and eliminating poverty, officials in cities with poor counties need to adopt a more nuanced approach that balances

[18] Cities that are not included in the China Data Lab COVID-19 case tally are shown as gray.

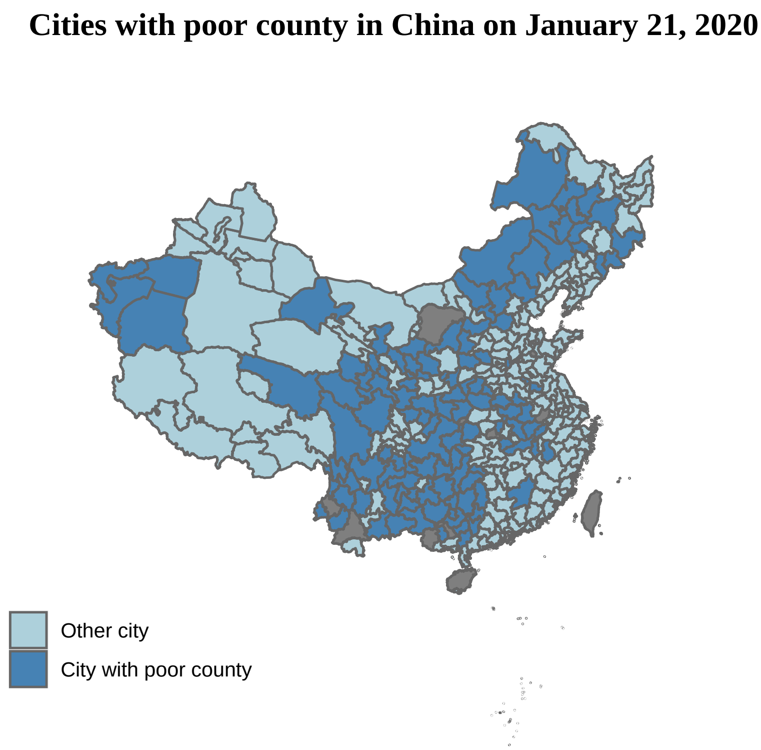

Figure 2: Officially designated “poor counties” in China’ s cities, January 21, 2020

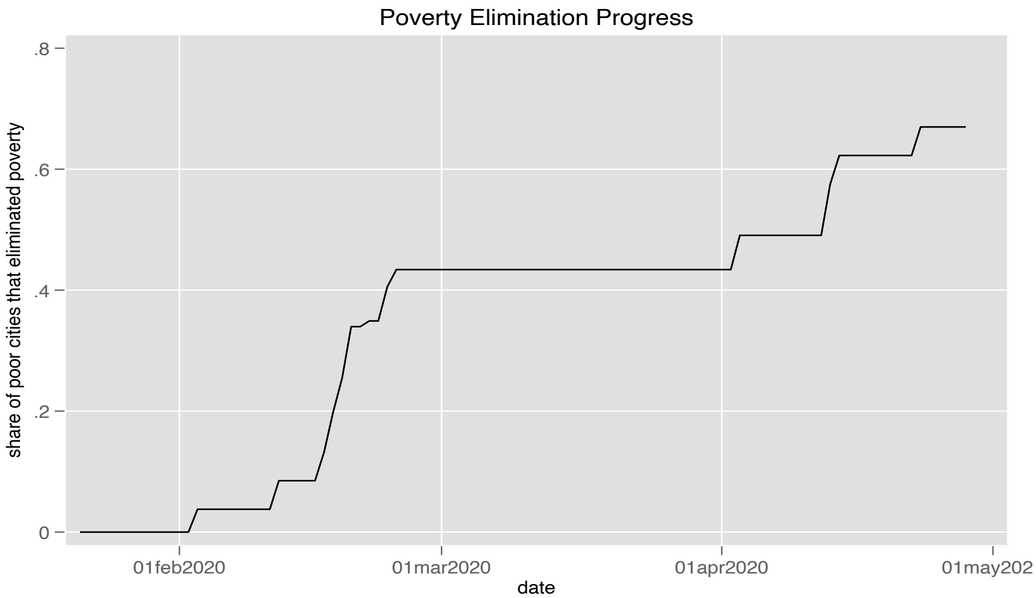

Figure 3: Poverty Elimination Progress
Note: Denominator is the number of cities with poor counties on Jan 21, 2020, while nominator is the number of cities that eliminated poverty since Jan 21, 2020.

both objectives.

Analyzing the onset of the two goals is challenging as the zero-COVID objective is determined at the national level without regional variation, while the poverty eradication goal was in place before the pandemic and analysis period. Instead, it would be more productive to examine the effects of removing each goal. If officials change their decision-making after the removal of a conflicting goal, it can be concluded that the removed goal influenced their decisions beforehand.

According to the theory, officials will strive for balance in their approach to these conflicting goals. However, once poverty elimination is achieved, cities with poor counties are likely to revert to a singular focus on zero COVID cases, leading local officials to prioritize pandemic control without considering other factors. This would reverse the previously balanced approach to local pandemic control.

Hypothesis 1: Cities that recently completed poverty elimination will impose stricter lockdowns in response to local infections.

According to my theory, the goals of zero-COVID and poverty reduction are not considered distinct, and therefore, reaching one goal will have a symmetrical impact on the other. In cities with poor counties, once the zero-COVID goal is met, it is likely that there will be a faster restart of economic activity. This can be evidence that city officials prioritize maintaining the economy and that the zero-COVID goal was hindering poverty reduction.

Hypothesis 2: Cities with poor counties will reopen faster than other cities when they achieve zero-COVID.

Similarly, they should adopt a more balanced approach to deal with sudden outbreaks as well:

Hypothesis 3: Cities with poor counties will lockdown slower than other cities when they detect the first COVID-19 case.

Empirical Strategy and Data

My study's unit of analysis is city-day, with a sample of 317 cities over 99 days starting from January 21, 2020 when human-to-human transmission of COVID-19 was confirmed by the Chinese government, until April 28, 2020, when the first wave of the pandemic was suppressed nationwide and poverty was eliminated in 70% of the poor cities. The analysis excludes Hubei Province, where Wuhan is located, due to direct involvement of the party center in its decisions (detailed description of city samples in Table A.4). The first wave of the pandemic was chosen for analysis due to several reasons: (1) High public compliance and approval of the lockdown was assumed during this period, and the assumption became less valid as frustration and grievances against the lockdown began to arise, particularly the public outcry for the poorly managed Shulan lockdown in May 2020. (2) Once poverty elimination was completed in most cities, pandemic control became the primary goal. (3) The policy room for local discretion in pandemic control reduced considerably when the coronavirus mutated into more contagious versions in late 2021 and the feasibility of balancing disappeared.

The primary dependent variable in this analysis is the implementation of new lockdown measures, as represented by changes in intra-city mobility. A tightening of lockdown measures in a city leads to a decrease in mobility, resulting in a negative change in mobility. The choice to focus on the change in mobility rather than mobility itself was made for theoretical, not methodological, reasons. Mobility reflects the outcome of all previous lockdown measures, while changes in mobility reflect daily decisions made by local governments in response to new infection cases. As this study focuses on local government decision making, changes in mobility provide a more relevant representation of the topic.

Because city leaders make their lockdown decisions based primarily on COVID-19 cases, my variable of interest is the interaction between the risk of local COVID-19 outbreak and poverty elimination status of the city.

The main variable to assess the risk of a local COVID-19 outbreak is the logarithmic level of infections in the city on the previous day. In addition, I consider alternatives such as the decline and resurgence of outbreak risk. To measure the goal of reaching zero-COVID, I create a binary variable to indicate whether the city has recorded zero local infections for three consecutive days following an outbreak. The third day of zero infections is considered the day the city achieved the zero-COVID target. To measure the resurgence of outbreak risk, I create a binary variable indicating whether the city reports its first COVID-19 case after having recorded zero cases in the preceding three days.

Poverty elimination status of the city is whether all counties in the city has been approved by the upper-level governments to exit the designation of "poor county." The timing of the provincial government' s announcement of approval is exogenous to city leaders and depends on the provincial government' s agenda and their irregular inspections. Moreover, since the dates of the public notification period are used instead of the later official change in poverty status, there is no substantive policy difference between the timing before and after the public announcement, except for the perception of the city leader. Any discontinuity in mobility around the dates should be due solely to the information effect of the announcement on the decision making of the city leader.

The change in mobility results from changes in citizen willingness to move and change in lockdown severity (whichever is lower). Since the paper is only concerned about the latter, the former should be controlled. Citizen willingness to move is largely captured by the risk of local outbreak, as the new virus was believed to be fatal in early 2020. To address remaining concerns, I control for daily weather variables of precipitation and temperature.

Intracity mobility data is available on Baidu. Baidu uses location data from Baidu Location-Based Service (LBS), including Baidu Maps, a popular Chinese equivalent of Google Maps, and applications that collect and send users' location data to Baidu. LBS receives 120 billion service requests daily from 1.1 billion monthly active devices. The intensity of intra-city mobility is measured as the proportion of city residents who "make a trip." A trip is identified through an origin-destination inference algorithm (Mohammed and Oke 2022) [19]. By using Density-based spatial clustering (Ester et al. 1996), Baidu analyses the location points of users to generate clusters where points are tightly packed, subject to a set of predefined parameters: minimum points to constitute a cluster and a distance threshold. If the user stays in a cluster for a certain period, the cluster is identified as a "stationary cluster." Stationary clusters are assigned as origins and destinations according to the temporal order, and a trip is identified. Baidu does not disclose specific parameter values of its algorithm, but its mobility data are widely used to gauge China's reopening and recovery by financial firms and media. As the data only capture users with a GPS device, it is not a complete measure of the entire population. However, the penetration rate of mobile internet reached 76 percent among the urban population of China in June 2020.[20] Since the analysis concentrates on intra-city mobility, the subset is large enough to represent most of the urban population.

Daily case data from COVID-19, precipitation, and temperature are from Harvard Dataverse's China Data Lab. I collect all public notification dates of poverty elimination from January 21, 2020 to April 28, 2020. Summary statistics are reported in Table A.2.

The level of analysis of this paper is city-level.[21] The city is the critical administrative level for

[19] "基于百度慧眼 OD 大数据的用地出行率指标计算," Baidu. https://baijiahao.baidu.com/s?id=1651370275127564535

[20] "第 46 次中国互联网发展状况统计报告," CNNIC, www.gov.cn/xinwen/2020-09/29/5548176/files/1c6b4a2ae06c4ffc8bccb49da353495e.pdf

[21] Four municipalities are included for their comparable sizes with prefectural cities, but results are robust without them.

determining the scope of lockdowns. As discussed in Section 3, all levels of government have the autonomy to decide on the pandemic control measure in their jurisdictions. Due to overlapping jurisdiction in a hierarchical administrative system, every decision is a mix of local judgments and upper-level intervention. The degree of upper-level intervention depends on the scale of the outbreak and its spillover effects. When an outbreak spills over to the whole country, the national government intervenes and pours national resources to suppress it, as was in the cases of Wuhan in 2020. Since the scale of outbreaks in early 2020 outside Hubei Province was usually confined to parts of a city,[22] the degree of autonomy is significantly higher for city governments than for county governments. Indeed, lockdowns were usually imposed by city governments on specific counties or urban districts. For example, 18 out of 25 cases in Hechi city's outbreak were recorded in Du'an, one of the seven poor counties in Hechi. Three city leaders and over one hundred security personnel were sent down to the county to supervise the lockdown.[23] Meanwhile, Hechi city was providing subsidies for firms in low-risk counties and districts to resume work.[24]

The city is also the critical administrative level for the treatment of poverty elimination status. Firstly, all poor counties need to pass a preliminary examination by their upper-level city government (市级初审) before applying for provincial approval. Provinces and the State Council will send down inspection teams irregularly (不定期巡查) and sometimes in secret (暗访) to verify results. All poor counties approved during the analysis period applied in 2019. In other words, poor county leaders have already secured their immediate superiors' approval. The poor city leaders who vouched for their inferiors faced uncertainty from their immediate superiors. Secondly, the effective treatment level is at the city level. From January 21, 2020, to April 28, 2020, each of the 65 cities achieved poverty elimination by having all of their poor counties exit the poverty designation on the same day.[25]

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[22]The median total infection for cities outside Hubei in the period was 15, and 95 percent of them recorded fewer than 162 cases in total.

[23]*China News*, www.chinanews.com.cn/sh/2020/02-22/9101256.shtml

[24]Hechi Human Resource and Social Security Bureau. rsj.hechi.gov.cn/zwdt/t2861087.shtml

[25]Another 14 cities had just a proportion of their poor counties approved. They still needed to strive for

Authoritarian officials are found to report fake statistics and deceive both the public and their superiors (Wallace 2016). This is less of a concern for this paper because the dependent variable, daily mobility, is collected and provided by a private company. Moreover, despite early cover-ups by local officials in Wuhan, it was extremely difficult to conceal COVID-19 infection cases as they would eventually spread to other localities. Since each locality tracked the source of each case found, suppressing reports from neighboring localities could be easily uncovered. Most countries experienced under-reporting due to testing capacity during the pandemic, but all cities outside of Hubei suppressed daily cases below one hundred in the dataset[26], so testing capacity was never strained. As for poverty reduction metric, my theoretical interest is the announcement of poverty elimination as a measure of officials' conflicting goals instead of substantiated poverty incidence *per se*, such that the authenticity of anti-poverty progress does not pose an analytical problem.

Finally, it is possible that all levels of governments collude to deceive the center such that poverty elimination must be completed on time. Provincial governments may relax the inspection standards and approve every application. Given the fact that every poor county exited poverty by November 23, 2020, this is a valid concern. However, this kind of collusion biases *against* my results such that the more city leaders are certain of the approval, the less likely my test of provincial approval's effect will change city leaders' decisions. Moreover, the random inspection of the State Council poses a threat to all levels of governments that some real changes need to made on the ground and provincial approval would be held accountable.

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the poverty elimination goal, so they were not coded as having eliminated poverty.

[26]The only exception was the 201 cases reported by Jining city on February 20, 2020, due to a mass-spreading in prison.

Results

Heterogeneous Responses Within Poor Cities

I examine whether cities with poor counties deal with the pandemic differently than they did in the past, after the provincial government approves their status of poverty elimination. If the exogenous process of removing poverty status affects pandemic response, then we can be sure that the goal of eliminating poverty interferes with pandemic response.

I estimate the following Model (1)(regression results reported in Table A.3):

$$
\begin{aligned}
MobilityChange_{it} = \theta_0 log(infection)_{i,t-1} \\
+ \sum_{\tau<-7,\tau=-7}^{+7,>7} \zeta_\tau \tau DaysAfterElimination_{it} \\
+ \sum_{\tau<-7,\tau=-7}^{+7,>7} \gamma_\tau \tau DaysAfterElimination_{it} \times log(infection)_{i,t-1} \\
+ \boldsymbol{\gamma} log(infection)_{i,t-1} \times EconomicStructure_i \\
+ X_{it}\boldsymbol{\beta} + \eta_i + \lambda_t + \epsilon_{it}
\end{aligned}
$$

where days after elimination is a set of indicator variables of whether city i is days after its exit poverty status announcement on date t. The elimination day is set as the default. I expect indicator variables of days before poverty elimination not to influence mobility restrictions and indicator variables of days after poverty elimination to significantly accelerate the imposition of mobility restrictions. The city fixed effects η_i capture the time-invariant heterogeneity across cities, and the date fixed effects λ_t capture time-varying shocks that took place nationally, such as the changing pandemic situation and national policies.

X is a vector of time-varying weather covariates, including change in daily precipitation and change in daily temperatures of city i on date t. They are included to control for non-policy-driven mobility change. Standard errors ϵ_{it} are clustered at the city level, the level of treatment.

Figure 4 plots the dynamic effects estimated in Model (1) above. The cities that were granted

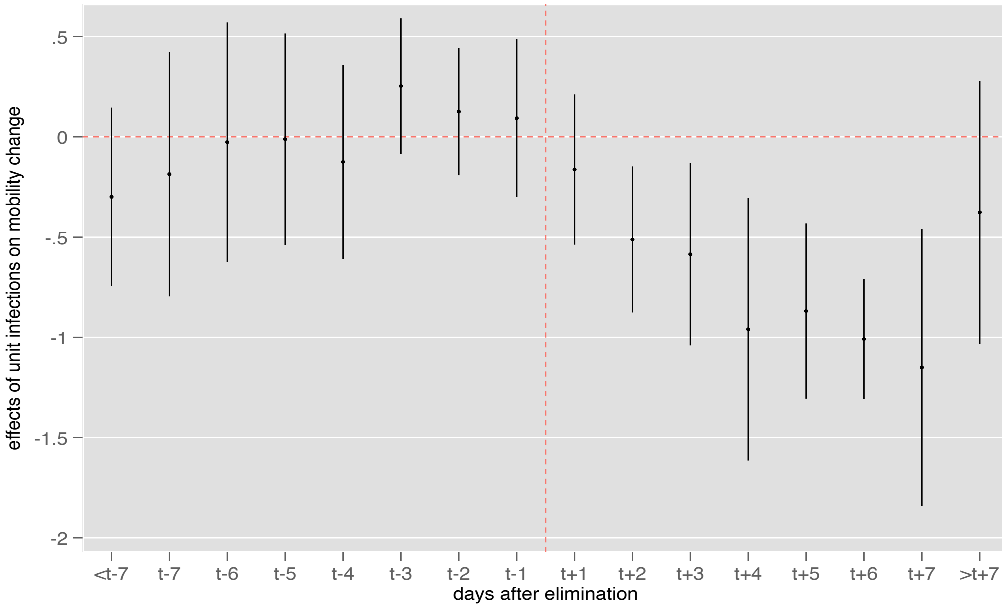

Figure 4: Quicker and more severe lockdowns after poverty elimination

Note: The figure plots coefficients on the interaction of τ Days after poverty elimination and log(infection). Dependent variable is mobility change. Only poor cities on Jan 21 are included. 95% confidence interval.

poverty exit by the provincial government ("new graduates") imposed lockdown measures similar to other cities with poor counties in response to unit infection prior to poverty elimination. The pattern illustrates that the assumption of parallel trends between new graduate cities and other cities with poor counties holds. Immediately after being approved to exit poverty, new graduates imposed significantly stricter lockdown measures in response to unit infection in the first week. The significant difference between new graduates and other cities with poor counties shows that the former impose lockdown measures more quickly after detecting unit infection.

It is expected that the difference in unit infection's mobility reduction effect between new graduate cities and other poor cities revert back to zero after a few days of poverty elimination. As shown in Figure 4, difference between two groups of cities after seven days of elimination is not different from zero. This is because new graduate cities can only impose a finite level of new mobility constraints before they reach total lockdown, where mobility stabilizes at a lower level than other cities. Note that the difference in mobility *change* does not bounce back to positive in the long run such that new graduates never catch up with other cities with poor counties in mobility *level*.

It may be that cities that still have poor counties took smaller but more persistent steps to impose lockdown measures that cumulatively pushed mobility to similarly low levels. Figure 4 shows this is not the case. The difference in lockdown severity depends on whether the *area* between the x-axis and the estimates is a net negative after t. Since new graduates consistently had more negative mobility changes than other cities with poor counties after discovering unit infection, the *area* is unambiguously negative, so new graduate cities did suppress mobility more.

Since the treatment (graduating from poverty) turns on at different times in different cities, I estimate a staggered difference-in-differences(DiD) Model(2) (reported in Table 1):

$$\begin{aligned} MobilityChange_{it} &= \theta_0 log(infection)_{i,t-1} \\ &+\zeta AfterElimination_{it} \\ +\theta_1 AfterElimination_{it} &\times log(infection)_{i,t-1} \\ +\gamma log(infection)_{i,t-1} &\times EconomicStructure_i \\ &+X_{it}\boldsymbol{\beta} + \eta_i + \lambda_t + \epsilon_{it} \end{aligned}$$

where $AfterElimination_{it}$ is a time-varying indicator variable that takes value 1 after the city i eliminated poverty, and $EconomicStructure_i$ denotes a vector of time-invariant economic indicators like GDP per capita and service sector share.

Table 1 shows consistent results with the event study in Figure 4: new graduate cities reduced intra-city mobility more than other cities with poor counties in response to unit infection. Goodman-Bacon (2021) finds two-way fixed effects DiD tend to produce biased results for staggered treatments unless treatment effects are constant over time and parallel trends assumption holds. I implement the Callaway and Sant’ Anna (2021) estimator to address this problem and find that the average treatment effect of poverty elimination is consistently negative and significant for the first three days after poverty elimination(Figure A.1). Note that this does not mean the difference is only short-term: the cumulative mobility change would remain negative as long as the average

Table 1: **Staggered DiD of Poverty Elimination**

	(1)	(2)	(3)
	D.Mobility	D.Mobility	D.Mobility
Previous day log(Infection)	-4.640*	-4.995*	-5.132*
	(1.128)	(1.410)	(1.433)
After Poverty Elimination	0.162*	0.300*	0.272*
	(0.049)	(0.114)	(0.112)
Poverty Elim.*log(Infection)	-0.670*	-0.702*	-0.727*
	(0.104)	(0.115)	(0.119)
GDP/capita*log(Infection)	0.296*	0.317*	0.323*
	(0.114)	(0.140)	(0.142)
Service share*log(Infection)	0.022*	0.025*	0.027*
	(0.006)	(0.007)	(0.007)
Constant	-0.149*	-0.202*	-0.205*
	(0.021)	(0.047)	(0.047)
Date FE	Yes	Yes	Yes
City FE	No	Yes	Yes
Weather	No	No	Yes
Observations	7421	7421	7223
R-squared	0.797	0.798	0.802
R-squared (Within)	0.043	0.042	0.060

Notes: Standard errors clustered around cities. Only cities that have poor counties on Jan 21 are included. Hubei Province is excluded. * $p < 0.05$

effect does not become positive to wind back the previous mobility restrictions.

Heterogeneous Responses Across City Groups

Now that we establish that cities with poor counties moderate their responses because of the trade-off of poverty reduction, do they respond differently to the pandemic than richer cities that had no political trade-off in the first place? Since cities with poor counties are likely to be categorically different from richer cities, this analysis aims to exclude some mechanical mechanisms and provide suggestive evidence that poverty elimination targets have an impact independent from economic devleopment level.

Model (3) is formulated as follows:

$$\begin{aligned} MobilityChange_{it} = \sum_{\tau=-4,0_1,0_2,0_3}^{+7} \theta_\tau \tau DaysAfterZeroCovid_{it} \\ +\zeta_1 PoorCity_{it} + \sum_{\tau=-4,0_1,0_2,0_3}^{+7} \beta_\tau \tau DaysAfterZeroCovid_{it} \times PoorCity_{it} \\ +\alpha log(infection)_{i,t-1} + \boldsymbol{\gamma} log(infection)_{i,t-1} \times EconomicStructure_i \\ +X_{it}\boldsymbol{\beta} + \eta_i + \lambda_t + \epsilon_{it} \end{aligned}$$

where $PoorCity_{it}$ denotes whether city i is a city with poor counties at date t, and $EconomicStructure_i$ denotes a vector of time-invariant economic indicators like GDP per capita and service sector share. $\tau DaysAfterZeroCovid_{it}$ denotes whether date t is τ days after achieving zero-COVID after an outbreak[27]. $\tau = 0_1$, 0_2, and 0_3 for the three zero-COVID days. Four pre-zero-COVID days and three zero-COVID days are included to match the seven post-zero-COVID days but the results are robust to other specifications. To control for mechanical factors for which different economic structures may lead to different COVID-19 responses, I include interaction terms of economic indicators and daily infections to allow for cities with different economic structures responding to outbreaks differently.

[27]Zero-COVID days are identified by finding three days with zero case after a day with non-zero case.

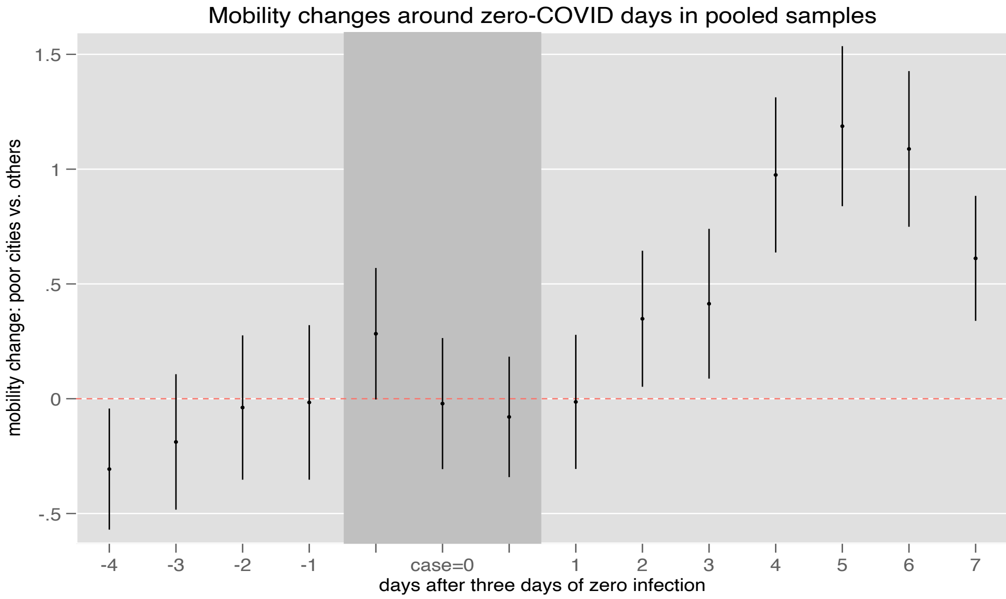

Figure 5: Poor cities reopen faster than others after zero-COVID
Note: This figure plots coefficients on the interaction of τ days after achieving three zero-COVID days after an outbreak and poverty elimination status. Dependent variable is mobility change. 95% confidence interval.

Figure 5 (Model(3), regression results reported in Table A.5(3)) compares the two groups of cities by estimating the effects of poverty status on the change in mobility before and after the city achieved zero-COVID. GDP per capita and service sector share are controlled. The y-axis represents the difference in mobility change on each day, which effectively measures the disparity in the speed of lockdown and reopening. Positive coefficients after $\tau = 2$ indicate that poor cities consistently outpace other cities in terms of reopening after achieving zero-COVID. Note that the pre-zero-COVID trends of the two city groups are not exactly parallel, as evidenced by significant differences at $\tau = -4$ and $\tau = 0_1$. However, the net difference pre-zero-COVID is approximately zero. On the other hand, post-zero-COVID differences consistently and substantially exceed zero, indicating a qualitative change in trend.

Similar results are found when the first COVID-19 case was detected in a city. Figure 6 (model in A.5; results in Table A.6 (3)) compares the two groups of cities by estimating the effects of poverty status on the change in mobility before and after the city found the first case. GDP per

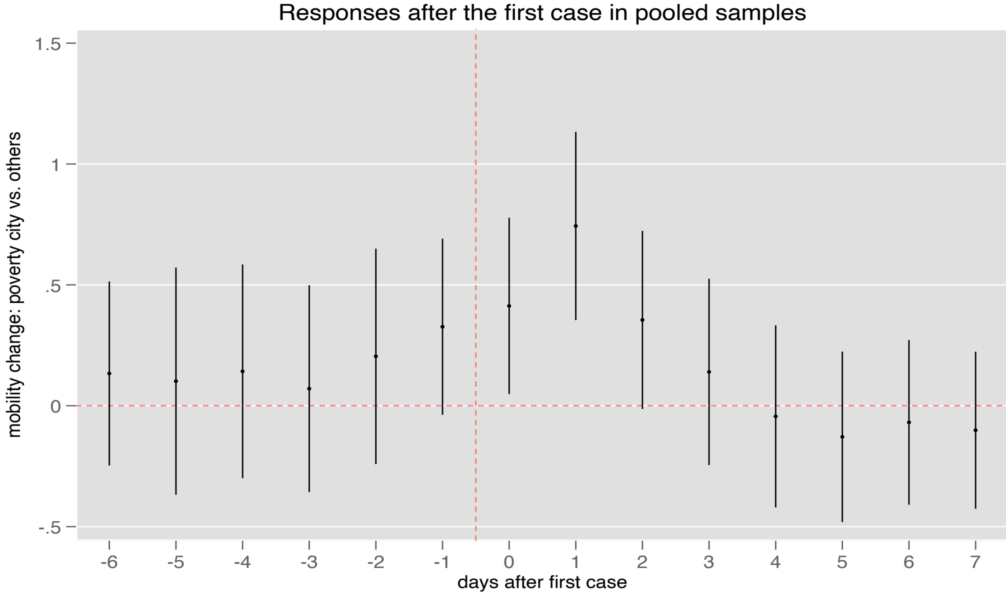

Figure 6: More moderate lockdown in poor cities after the first case
Note: Coefficients on the interaction of τ days after detecting first COVID and poverty elimination status are plotted. 95% confidence interval.

capita and service sector share are controlled. Positive values of coefficients show that poor cities are imposing fewer mobility restrictions than other cities on each day in the first three days after the first COVID case. Note poor cities did not impose more restrictions thereafter such that their cumulative mobility restrictions would stay fewer than other cities after the first few days, even when their *speed* of lockdown converged with other cities after $\tau = 3$. This is also illustrated by the *area* between the x-axis and the estimates is net positive, so cities with poor counties did suppress mobility less than other cities.

Discussion

Taking these figures together, a recurring pattern of bureaucratic multitasking emerges: conflicting goals balance each other out. Officials sacrifice the economy to achieve the goal of zero-COVID, and they moderate closures to avoid sabotaging poverty eradication too much. Moreover, despite the interference and moderation, cities with poor counties in China achieved both goals without cutting corners: they achieved zero-COVID with fewer lockdowns. The poverty elimination target became an advantage: poor cities that achieved poverty elimination targets later (after April 28) had higher GDP growth rates in 2020 than those that finished earlier (Table A.7). Meanwhile, these cities did not suffer from higher cases per capita either (Table A.8), despite their lack of medical resources and lenient control. In the context of China in 2020, it is also plausible that officials with poverty goals can push back public or political pressure for them to impose excessive lockdowns by pointing to the importance of poverty elimination. Conflicting targets force/afford officials to implement more efficient policies that made the tradeoff between the economy and public health less acute.

Contrary to the theoretical expectation that conflicting goals are self-defeating and that agents will not distribute their efforts so that they cancel each other out, conflicting goals lead to more balanced implementation. Agents have an incentive to find better ways to offset the damage that one goal does to the other goal. Agents, here poor city officials, were forced to find an interior solution that allocates effective efforts toward both goals.

It is possible that cities with poor counties impose fewer lockdowns because provincial governments direct them to avoid lockdowns, and local officials are simply heeding top-down guidance. While there is no public document to prohibit any jurisdiction from imposing lockdown measures, it is hard to exclude the possibility of internal communication in some places. However, a city-wide outbreak can quickly escalate into a province-wide epidemic, while poverty elimination in a city is an isolated matter and ultimately subject to provincial approval. Therefore, the relative importance of poverty elimination is apparently higher for the city government than the provincial government, making it implausible that provinces needed to strike a balance for cities in favor of poverty elimination. As the case of Hechi city's outbreak shows, the upper-level intervention, if any, was to pressure quicker suppression of the outbreak instead of forestalling lockdown. The only mention of the provincial-level Guangxi government, the upper-level unit above Hechi, was about its help and instructions in suppressing the outbreak instead of emphasizing poverty alleviation[28]. And Hechi's poor counties were not exempted from lockdown when they had an outbreak: city officials punished Du'an's (the poor county with an outbreak) officials and directly supervised Du'an's

[28] *China News*, www.chinanews.com.cn/sh/2020/02-22/9101256.shtml

lockdown for weeks while letting the rest of the city reopen[29].

Alternatively, poor cities may reopen faster due to resource constraints, as they cannot afford to implement longer lockdown measures. However, this explanation is ruled out by controlling for economic structures such as GDP per capita and the share of the service sector. In fact, a higher GDP per capita consistently correlates with fewer lockdowns, both among poor cities and other cities (Table A.9). This indicates that it is the richer cities that can afford to implement moderate and precise control measures. Without considering poverty targets, less developed cities would have imposed even more severe lockdowns than their wealthier counterparts, as shown by the main results indicating that cities tighten pandemic control after poverty elimination. To address any remaining concerns, such as the possibility of poor cities inherently having lower mobility and mobility changes, I also normalize each city's mobility measure with its pre-pandemic mobility level.

The scope condition regarding the feasibility of balanced efforts suggests that the moderation effect may be weaker in cities where achieving both goals is less feasible. To explore this further, I examine the impact of poverty eradication progress on pandemic response, specifically by considering the proportion of poor counties within a city's jurisdiction. Surprisingly, the findings in Table A.10 provide suggestive evidence that cities with a higher proportion of poor counties tend to implement less stringent COVID-19 lockdown measures than other poor cities. This finding does not lend support to the assumption that these cities should believe it's less feasible to eradicate poverty in the near future so balancing is not meaningful. However, it aligns with the other scope condition of comparable importance. In such cases, agents prioritize the goal that lags behind, as its urgency automatically lends it importance. Agents strategically hedge their performance to navigate the challenges of pursuing multiple goals concurrently.

Conclusion

Formal institutions, such as budgetary oversight by elected representatives or social interest groups, as well as informal institutions, like patron-client trust, play a crucial role in improving policy imple-

[29] Hechi Human Resource and Social Security Bureau. rsj.hechi.gov.cn/zwdt/t2861087.shtml

mentation by addressing commitment and information problems. However, it is equally important to consider the substantive configuration of other goals within higher-order incentive structures as a mechanism of policy implementation. This paper sheds light on the significance of conflicting goals that are both feasible to balance and of comparable importance. These conflicting goals can effectively constrain agents from pursuing a single goal at any cost and instead encourage them to seek more efficient balances. The objective of achieving balance becomes particularly relevant when we challenge the assumption that complete compliance is always desirable and recognize the problematic nature of overcompliance.

Using the example of local government responses to the COVID-19 pandemic, empirical analysis in this paper uses event studies and staggered DiD to show the presence of conflicting goals related to poverty elimination leads to a remarkable 40 percent reduction in the severity of COVID-19 lockdowns in cities under poverty elimination target, compared to a counterfactual scenario where poverty alleviation evaluation was not a factor. Event studies leveraging the timing achieving zero COVID and detecting the first COVID case also find evidence that richer cities without poverty elimination targets systematically lockdown more and reopen slower than cities under poverty elimination targets, even after controlling their respective economic development level and economic structure.

This paper makes several significant contributions to the literature. It adds to our understanding to policy implementation by highlighting the role of configuration of goals as a mechanism to constrain bureaucratic behaviors, alongside formal and informal institutions. It emphasizes that agent behaviors under each contract are not solely influenced by the rules of that specific contract, but also by the configurations of other contracts they are subject to. While previous research on policy implementation has often focused on examining constraints imposed by the rules and structures of a contract and its goal in isolation, this paper highlights the critical significance of considering the externalities that arise from the interplay between different goals.

Second, this paper contributes to the literature on multitasking and principal-agent relations by demonstrating the advantages of conflicting goals under an alternative objective function of avoiding overcompliance. It highlights that the pursuit of balanced efforts among conflicting goals can be beneficial compared to single-tasking approaches. This finding is particularly relevant in complex environments where the full compliance of social policies frequently results in unintended consequences that are not socially desirable.

Third, the paper builds on the existing literature of China's policy implementation by exploring the changing incentive structure. High-powered incentives and over-compliance that ensues have led to dire consequences such as environmental degradation, rising local government debt, and the construction of empty cities. Additionally, the increasing frequency of political punishments has created a climate in which officials face the constant threat of sanctions for failures, which can serve as a stronger motivator than the desire for promotion and further exacerbate the issue of over-compliance. However, this paper provides some consolation by suggesting that the proliferation of the threat of sanctions may itself serve as a mechanism to control over-compliance.

Finally, the findings of this paper raise important questions regarding the evaluation of China's Zero-COVID policy. While China's stringent lockdown measures played a crucial role in controlling the spread of the pandemic within its borders, they also resulted in significant socio-economic costs that ultimately contributed to the downfall of the Zero-COVID policy in late 2022. This raises the question of whether all of these lockdowns were necessary, considering the immense social and economic consequences they entailed. The results presented in this paper indicate that, at least in 2020, even local officials in resource-constrained poor cities were able to implement fewer lockdown measures and effectively manage the outbreak. This suggests that factors such as political survival incentives rather than solely relying on public health knowledge may have influenced the decision-making process regarding lockdown measures. This finding emphasizes the need to critically examine the motivations and factors driving lockdown decisions, particularly in the context of achieving a balance between public health objectives and minimizing socio-economic costs.

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Appendix

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A.1 Symmetric Contract

The principal assigns two tasks A and B to a single agent. The principal commits to a contract that rewards the agent with an ex-post payment after the completion of the two tasks.

According to Bolton and Dewatripont (2004: 224) the optimal contract should be: $\Gamma = \{\gamma^{00}, \gamma^{01}, \gamma^{10}, \gamma^{11}\}$ with $\gamma^{11} > \gamma^{00} = \gamma^{01} = \gamma^{10} = 0$ where γ^{00} denotes the ex-post payment for failing both tasks, γ^{01} denotes the payment for failing task 1 and succeeding task 2, γ^{10} denotes the payment for failing task 2 and succeeding task 1, and γ^{11} denotes the payment for succeeding both.

The contract is symmetric, such that both tasks have the same priority and failing either one means zero reward.

The agent chooses a policy p from a policy space $[0, 1]$ to maximize the expected ex-post payment $E(y|p)$. The probabilities of completing A or B are functions of p. A and B are conflicting tasks such that p affects them in opposite directions. Since the budget is soft, the maximization of the probabilities of completing A or B is not subject to any external constraints.

Let

$$\alpha = Pr(A|p) = \theta p^a, \tag{1}$$

$$\beta = Pr(B|p) = \delta(1-p)^b, \tag{2}$$

where $a < 1, b < 1, \theta \in N, \delta \in N$ are exogenous parameters that determine the substitution rate between A and B.

Then the expected payment is:

$$\begin{aligned} E(y|p) &= \alpha\beta\gamma^{11} + \alpha(1-\beta)\gamma^{10} + (1-\alpha)\beta\gamma^{01} + (1-\alpha)(1-\beta)\gamma^{00} \\ &= \alpha\beta\gamma^{11} \end{aligned} \tag{3}$$

The agent chooses p to maximize $E(y|p)$:

$$\max_p E(y|p) = \alpha(p)\beta(p)\gamma^{11} \tag{4}$$

The first order condition is:

$$\frac{\partial E(y|p^*)}{\partial p} = (\frac{\partial \alpha}{\partial p}\beta + \alpha\frac{\partial \beta}{\partial p})\gamma 11 = 0 \tag{5}$$

$$\frac{\frac{\partial \alpha}{\partial p}}{\frac{\partial \beta}{\partial - p}} = \frac{\alpha(p^*)}{\beta(p^*)} \tag{6}$$

Note that $\alpha(p^*)$ and $\beta(p^*)$ are equilibrium success rates of task A and B while $\frac{\frac{\partial \alpha}{\partial p}}{\frac{\partial \beta}{\partial - p}}$ is the substitution rate between A and B.

Substituting equations (1) and (2) into the (6) to solve p^*:

$$\begin{aligned} \frac{\frac{\partial \alpha}{\partial p}}{\frac{\partial \beta}{\partial - p}} = \frac{a}{b}\frac{\theta}{\delta}\frac{p^{a-1}}{(1-p)^{b-1}} &= \frac{\theta}{\delta}\frac{p^a}{(1-p)^b} = \frac{\alpha(p)}{\beta(p)} \\ \frac{1-p}{p} &= \frac{b}{a} \\ p^* &= \frac{a}{a+b} \\ 1-p^* &= \frac{b}{a+b} \end{aligned}$$

Therefore, the optimal policy choice for the multitask agent is to prioritize the task with higher return to the policy. Deducing from the first-order condition of compensation maximization, the equilibrium success rates of the two tasks should reflect the substitution rate between them.

For the optimal solution p^*, the agent needs to use exogenous parameters, such as a and b, tasks A and B' s returns to the policy p. A2 shows that an asymmetric contract would make conflicting goals less effective to balance efforts and force the agents to weigh trade-offs.

A.2 Asymmetric Multitask Contract

An asymmetric multitask contract $\Gamma = \{\gamma^{00}, \gamma^{01}, \gamma^{10}, \gamma^{11}\}$ satisfies $\gamma^{11} > \gamma^{10} > \gamma^{01} = \gamma^{00} = 0$. This means that the principal will still reward the completion of only task A but will not reward the completion of task B only. A clear priority is assigned to task A.

$$\begin{aligned} E(y|p) &= \alpha\beta\gamma^{11} + \alpha(1-\beta)\gamma^{10} + (1-\alpha)\beta\gamma^{01} + (1-\alpha)(1-\beta)\gamma^{00} \\ &= \alpha\beta\gamma^{11} + \alpha(1-\beta)\gamma^{10} \end{aligned} \tag{7}$$

The agent chooses p to maximize $E(y|p)$:

$$\max_p E(y|p) = \alpha(p)\beta(p)\gamma^{11} + \alpha(p)(1-\beta(p))\gamma^{10} \tag{8}$$

The first order condition is:

$$\frac{\partial E(y|p^*)}{\partial p} = (\frac{\partial \alpha}{\partial p}\beta + \alpha\frac{\partial \beta}{\partial p})\gamma 11 + \frac{\alpha}{p}\gamma^{10} + (\frac{\partial \alpha}{\partial p}\beta + \alpha\frac{\partial \beta}{\partial p})\gamma 10 = 0 \tag{9}$$

$$\beta = \frac{\frac{\partial \beta}{\partial -p}}{\frac{\partial \alpha}{\partial p}}\alpha - \frac{\gamma^{10}}{\gamma^{11} - \gamma^{10}} \tag{10}$$

To have an internal solution that exploits the exogenous parameter of substitution rate $\frac{\frac{\partial \alpha}{\partial p}}{\frac{\partial \beta}{\partial -p}}$ and actually multitask, β needs to be greater than zero or equal to it.

$$\frac{\frac{\partial \beta}{\partial -p}}{\frac{\partial \alpha}{\partial p}}\alpha - \frac{\gamma^{10}}{\gamma^{11} - \gamma^{10}} \geq 0 \tag{11}$$

$$\frac{\frac{\partial \beta}{\partial -p}}{\frac{\partial \alpha}{\partial p}}\alpha \geq \frac{\gamma^{10}}{\gamma^{11} - \gamma^{10}} \tag{12}$$

Substituting equations (1) and (2) into (12):

$$\frac{b\delta}{a}\frac{p^*}{(1-p^*)^{1-b}} \geq \frac{\gamma^{10}}{\gamma^{11}-\gamma^{10}} \tag{13}$$

The principal does not possess the information of substitution rate $\frac{\frac{\partial\beta}{\partial -p}}{\frac{\partial\alpha}{\partial p}}$ when they design the contract Γ. Therefore, they have to set γ^{10} low enough to ensure the agent multitask and weigh trade-offs. As $\gamma^{10} \to \gamma^{11}$, $p^* \to 1$, rendering exogenous parameters in equation (13) irrelevant. In the other words, asymmetry in the contract is distorting the agent' s informed decision-making. This also confirms that the principal should set γ^{10} to zero in an optimal contract.

A.3 Provincial People's Congress Dates

As Table A.1 shows, nearly all target-setting provincial People's Congress convened before Wuhan lockdown on January 23. Provincial approval may be issued during important political gatherings, such as plenary meetings of the provincial People' s Congress. Therefore, the timing of provincial approval may coincide with other political decisions, such as political turnover and the setting of developmental targets for the following year instead of the departure of poverty counties. The analysis of the plenary meetings of all provincial People' s Congress in 2020 revealed that all of them (except for Sichuan Province) took place before January 21, 2020. Therefore, other political decisions could not explain the variation between local responses after Wuhan lockdown on January 23.

Table A.1 : Opening Dates of Meetings of Provincial People' s Congress in 2020

Xinjiang	1/6	Shanxi	1/13
Hebei	1/7	Guangdong	1/14
Tibet	1/7	Liaoning	1/14
Gansu	1/10	Tianjin	1/14
Henan	1/10	Guizhou	1/15
Chongqing	1/11	Jiangsu	1/15
Fujian	1/11	Jiangxi	1/15
Anhui	1/12	Qinghai	1/15
Beijing	1/12	Shaanxi	1/15
Guangxi	1/12	Shanghai	1/15
Heilongjiang	1/12	Hainan	1/16
Hubei	1/12	Yunnan	1/17
Inner Mongolia	1/12	Shandong	1/18
Jilin	1/12	Ningxia	1/20
Zhejiang	1/12	Sichuan	5/9
Hunan	1/13		

A.4 Number of Cities in the Sample

	Number of Cities
Total Prefectural-level Cities in China + Four Municipalities	337
Sample Collected	330
Exclude Hubei (Sample used in 6.2)	317
Poor Cities on Jan 21	106
Exclude Hubei + Poor Cities on Jan 21 (Sample used in 6.1)	100
Exclude Hubei + New Graduate Cities during Jan 21-Apr 28	65
Exclude Hubei + Poor Cities on Apr 28	35

Table A.2 : Number of Cities in Analysis

A.5 Model of Figure 5

The comparison group in this model is days not in the proximity of First Covid. I do not include more than six days before or more than seven days after First Covid because First Covid date is not unique for each city such that such coding rule would make the same day coded in multiple ways in respect to different First Covid dates.

$$
\begin{aligned}
MobilityChange_{it} = \sum_{\tau=-6}^{+7} \theta_\tau \tau DaysAfterFirstCovid_{it} \\
+\zeta_1 PoorCity_{it} \\
+ \sum_{\tau=-6}^{+7} \beta_\tau \tau DaysAfterFirstCovid_{it} \times PoorCity_{it} \\
+ \sum_{\tau=0}^{7} \alpha_\tau log(infection)_{i,t-\tau} \\
+\boldsymbol{\gamma} log(infection)_{i,t-1} \times EconomicStructure_i \\
+X_{it}\boldsymbol{\beta} + \eta_i + \lambda_t + \epsilon_{it}
\end{aligned}
$$

A.6 Figures and Tables

Table A.3 : Summary Statistics

VARIABLES	N	Mean	SD	Min	Max
Change in 7-day M.A. in rel. mobility	33957	-0.07	2.36	-18.11	12.09
D.Precipitation (inches)	31383	0	0.33	-5.51	5.91
D.Temperature (Fahrenheit)	31383	0.31	5.08	-29.00	24.80
log(infections)	31522	0.15	0.47	0	5.31
Active poverty city	33957	0.19	0.40	0	1
After poverty elimination	33957	0.14	0.35	0	1
Achieve zero COVID	33998	0.02	0.13	0	1
Found first case	33998	0.02	0.13	0	1
log(GDP/capita)	27038	10.87	0.53	9.45	12.16
Service sector share	27038	46.72	8.40	26.54	80.98

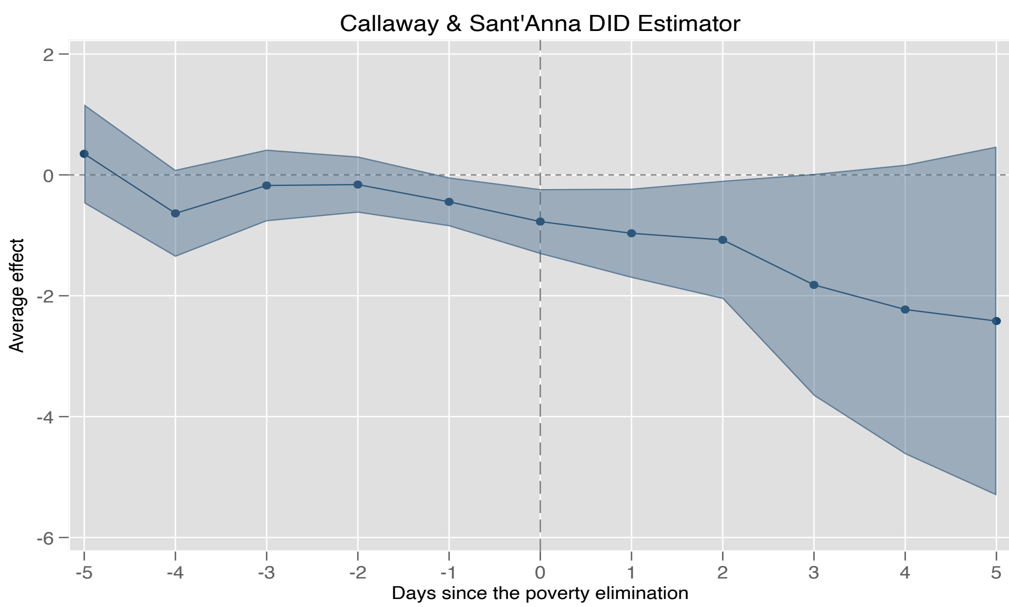

Figure A.1 : Callaway & Sant'Anna Estimator of Poverty Elimination×Outbreak

Note: Average effect of Outbreak×AfterPovertyElimination, estimated by using *csdid* package built upon Callaway and Sant' Anna (2021). Outbreak is a dummy variable taking value 1 if the city has non-zero COVID case on that day. Negative value means cities that eliminated poverty impose more mobility restrictions in an outbreak. Outbreak, After Poverty Elimination, Outbreak×log(GDP per capita), and Outbreak× Service share are included as controls. 95% confidence interval. Only poor cities on Jan 21 are included. Hubei Province is excluded.

Table A.4 : Regression Table of Figure 4

	(1) D.Mobility	(2) D.Mobility	(3) D.Mobility
Previous day log(Infection)	-3.534*	-3.994*	-4.030*
	(1.369)	(1.648)	(1.658)
t-3	0.096	0.126	0.253
	(0.169)	(0.170)	(0.169)
t-2	0.130	0.129	0.126
	(0.164)	(0.165)	(0.159)
t-1	0.067	0.052	0.093
	(0.207)	(0.216)	(0.198)
t+1	-0.218	-0.218	-0.163
	(0.215)	(0.207)	(0.188)
t+2	-0.514*	-0.503*	-0.512*
	(0.166)	(0.165)	(0.183)
t+3	-0.659*	-0.633*	-0.585*
	(0.236)	(0.232)	(0.228)
t+4	-0.945*	-0.936*	-0.960*
	(0.346)	(0.333)	(0.328)
t+5	-0.901*	-0.900*	-0.869*
	(0.201)	(0.199)	(0.219)
t+6	-0.893*	-0.919*	-1.009*
	(0.139)	(0.148)	(0.150)
t+7	-1.244*	-1.252*	-1.150*
	(0.320)	(0.309)	(0.346)
>t+7	-0.373	-0.410	-0.376
	(0.307)	(0.309)	(0.329)
Date FE	Yes	Yes	Yes
City FE	No	Yes	Yes
Weather	No	No	Yes
Observations	7223	7223	7223
R-squared	0.797	0.800	0.804
R-squared (Within)	0.044	0.049	0.068

Notes: Standard errors clustered around cities. Dates from January 21 to April 28. Only cities with poor counties on Jan 1 are included. Hubei Province is excluded. "t+n" indicates the interaction of n days from the Poverty Elimination announcement and previous day log(infection). <t-7 through t-4 are included but not reported. n days from the Poverty Elimination and interactions of log(infection) with Economic Structures are included but not reported. * $p < 0.05$

Table A.5 : Regression Table of Figure 5

	(1) Poverty Cities D.Mobility	(2) Other Cities D.Mobility	(3) All cities D.Mobility
t-4	-0.116	0.102	-0.343*
	(0.103)	(0.069)	(0.135)
t-3	-0.155	0.089	-0.227
	(0.116)	(0.078)	(0.154)
t-2	-0.130	0.016	-0.083
	(0.123)	(0.073)	(0.163)
t-1	-0.193	-0.095	-0.065
	(0.128)	(0.076)	(0.174)
t+1	-0.012	-0.181*	-0.057
	(0.113)	(0.070)	(0.143)
t+2	0.204	-0.126	0.306*
	(0.118)	(0.069)	(0.147)
t+3	0.297*	-0.029	0.372*
	(0.121)	(0.066)	(0.164)
t+4	0.378*	0.062	0.925*
	(0.122)	(0.065)	(0.170)
t+5	0.492*	0.140*	1.140*
	(0.117)	(0.061)	(0.175)
t+6	0.511*	0.176*	1.045*
	(0.107)	(0.056)	(0.170)
t+7	0.426*	0.148*	0.571*
	(0.093)	(0.055)	(0.136)
Date FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Weather	Yes	Yes	Yes
Economic Structure	No	No	Yes
Observations	10230	19251	24696
R-squared	0.752	0.747	0.780
R-squared (Within)	0.028	0.012	0.067

Notes: Standard errors clustered around cities. Dates from January 21 to April 28. Hubei Province is excluded. For Column 1 and 2, "t+n" indicates dummies of n days from the three-day zero case period. Column 3 reports results of Model (3), "t+n" indicates interactions of dummies of n days from the three-day zero case period and poverty city status. Three zero-COVID day dummies and interactions are included in all models and not reported. For Column 3, day dummies are included but not reported. Economic Structure indicates interactions of lagged infection case number with the city's GDP per capita and service sector share. Poor City dummy, log(infection), t-6, and t-5 are included but not reported. * $p < 0.05$

Table A.6 : Regression Table of Figure 6

	(1) Poverty Cities D.Mobility	(2) Other Cities D.Mobility	(3) All cities D.Mobility
t-4	-0.149	0.150	0.137
	(0.169)	(0.096)	(0.224)
t-3	-0.155	0.241*	0.064
	(0.161)	(0.105)	(0.213)
t-2	-0.144	0.181	0.197
	(0.166)	(0.110)	(0.227)
t-1	-0.145	0.047	0.319
	(0.136)	(0.106)	(0.187)
First COVID	-0.082	-0.189	0.405*
	(0.148)	(0.104)	(0.186)
t+1	-0.104	-0.536*	0.737*
	(0.159)	(0.101)	(0.200)
t+2	-0.354*	-0.785*	0.348
	(0.153)	(0.107)	(0.187)
t+3	-0.514*	-0.829*	0.133
	(0.152)	(0.098)	(0.189)
t+4	-0.694*	-0.860*	-0.051
	(0.164)	(0.098)	(0.186)
t+5	-0.629*	-0.769*	-0.135
	(0.158)	(0.092)	(0.173)
t+6	-0.579*	-0.746*	-0.074
	(0.133)	(0.084)	(0.167)
t+7	-0.632*	-0.581*	-0.106
	(0.115)	(0.079)	(0.162)
Date FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Weather	Yes	Yes	Yes
Economic Structure	No	No	Yes
Observations	9992	18615	24143
R-squared	0.768	0.765	0.793
R-squared (Within)	0.081	0.061	0.095

Notes: Standard errors clustered around cities. Dates from January 21 to April 28. Hubei Province is excluded. For Column 1 and 2, "t+n" indicates dummies of n days from the first COVID case date. Column 3 reports results of Model A.5, "t+n" indicates interactions of dummies of n days from the first COVID case and poverty city status. For Column 3, day dummies are included but not reported. Economic Structure indicates interactions of infection case number with the city's GDP per capita and service sector share. Poor City dummy, log(infection), t-6, and t-5 are included but not reported. * $p < 0.05$

Table A.7 : Lockdown Dampened 2020 GDP Growth

	GDP Growth			
	(1)	(2)	(3)	(4)
Poor City	-0.002	0.042*	0.038*	0.031*
	(0.007)	(0.007)	(0.008)	(0.009)
Poverty Elim. before April 28		-0.053*	-0.054*	-0.046*
		(0.011)	(0.011)	(0.011)
log(GDP/capita)			-0.005	-0.002
			(0.005)	(0.005)
Service Share				0.006
				(0.003)
Agr. Share				0.007
				(0.004)
Industrial Share				0.006
				(0.003)
Constant	1.027*	1.027*	1.083*	0.465
	(0.003)	(0.003)	(0.056)	(0.363)
Observations	286	286	280	258
R-squared	0.000	0.057	0.065	0.076

Notes: Standard errors clustered around cities. * $p < 0.05$

Table A.8 : Poverty cities do not have more cases

	(1) Total Case	(2) Total Case	(3) Total Case	(4) Total Case
Poverty City	-0.241	-0.253	0.159	0.239
	(0.311)	(0.221)	(0.159)	(0.201)
Poverty Elim. before April 28		0.015	0.123	0.169
		(0.162)	(0.119)	(0.146)
log(GDP/capita)			0.952	1.244
			(0.738)	(0.979)
Service Share				0.406
				(0.357)
Agr. Share				0.467
				(0.403)
Industrial Share				0.428
				(0.365)
Constant	0.532	0.531	-9.969	-55.008
	(0.290)	(0.294)	(7.849)	(46.293)
Observations	280	280	279	258
R-squared	0.001	0.001	0.017	0.026

Notes: Standard errors clustered around cities. * $p < 0.05$

Table A.9 : Lockdown Severity and Economic Structures

	(1) All cities	(2) Other cities	(3) Poor cities
Previous day log(Infection)	-8.527*	-10.172*	-9.840*
	(0.584)	(0.728)	(2.712)
log(GDP/capita)*log(Infection)	0.731*	0.889*	0.763*
	(0.059)	(0.071)	(0.256)
Service share*log(Infection)	0.003	-0.001	0.029*
	(0.003)	(0.003)	(0.012)
Constant	-0.057*	0.048*	-0.602*
	(0.006)	(0.007)	(0.016)
City FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Weather	Yes	Yes	Yes
Observations	26292	22067	4225
R-squared	0.774	0.770	0.822

Notes: Dependent variable is mobility change. Standard errors clustered around cities. Dates from January 21 to April 28. Hubei Province is excluded. * $p < 0.05$

Table A.10 : Poor County Share

	(1) D.Mobility	(2) D.Mobility
Previous day log(Infection)	-6.179*	-11.984*
	(1.286)	(2.428)
Poor County Share*log(Infection)	0.556*	0.713$^+$
	(0.274)	(0.416)
log(GDP/capita)*log(Infection)	0.413*	0.944*
	(0.128)	(0.232)
Service Share*log(infection)	0.026*	0.030*
	(0.006)	(0.011)
Poor County Share	0.066	0.261
	(0.118)	(0.443)
City FE	No	Yes
Date FE	Yes	Yes
Weather	Yes	Yes
Observations	4225	4225
R-squared	0.816	0.822
R-squared (Within)	0.059	0.057

Notes: Standard errors clustered around cities. Only Poor cities are included. Dates from January 21 to April 28. Hubei Province is excluded. $^+$ $p < 0.10$ * $p < 0.05$