Cheat and Get Promoted: The Political GDP Manipulation Cycle in China

Zekai Shen* Wentao Lu†

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Abstract

This paper investigates the existence of a political GDP manipulation cycle in China, where local officials falsify economic data to enhance their promotion prospects. Using a panel dataset of 330 Chinese prefecture-level cities from 1998 to 2020, we compare official GDP growth rates with growth rates derived from nighttime light satellite imagery to estimate the extent of data manipulation. We find that the discrepancy between the two measures of economic growth exhibits a significant increase in the years of the National Communist Party Congress (NCPC), suggesting a political cycle of GDP overstatement. Furthermore, while official data show a political business cycle with higher growth rates during NCPC years, nighttime light data indicate a significant decrease in economic activity during these periods. These findings challenge the conventional results about China's political business cycle.

Keywords: political business cycle, GDP manipulation, promotion incentive, nighttime light data, economic growth

*School of Economics, Singapore Management University (zekai.shen.2023@mse.smu.edu.sg)
†School of Economics, Singapore Management University (wentao.lu.2023@mse.smu.edu.sg)

1 Introduction

The political business cycle, a phenomenon characterized by economic fluctuations induced by the electoral cycle, has long been a topic of interest among economists and political scientists(Nordhaus, 1975; Dubois, 2016; Rogoff and Sibert, 1988). Incumbent politicians, driven by the desire to secure re-election, may opportunistically manipulate fiscal and monetary policies to boost short-term economic growth, even at the cost of long-term economic stability(Dubois, 2016). This opportunistic behavior is fueled by the short-sightedness of voters(Kramer, 1971; Brender and Drazen, 2005), who often place greater emphasis on recent economic performance when making voting decisions. Consequently, the political business cycle has been widely observed in various democratic countries(Aidt et al., 2011), particularly in developing economies(Shi and Svensson, 2006).

In China, where the government exerts substantial control over the economy(Ferreira et al., 2013; Lyu et al., 2018), the political business cycle is likely to be even more pronounced. Local government officials, whose career advancement is largely determined by their performance in promoting economic growth and maintaining social stability(Xu, 2011), have strong incentives to stimulate the economy prior to personnel changes(Zhou, 2007; Zhang and Gao, 2007). This politically driven economic expansion has been found to influence not only traditional economic indicators(Xi et al., 2018) but also a wide range of social and environmental factors, such as fiscal expenditure(Guo, 2009), land allocation(Yu et al., 2015), resource misallocation(Zhou et al., 2013), pollution(Tian and Tian, 2021), and workplace safety(Shi and Xi, 2018; Nie et al., 2013).

However, the existing literature on China's political business cycle overlooks a critical issue: the reliability of official economic data. Numerous studies have suggested that China's reported GDP growth rates are overstated(Lyu et al., 2018; Rawski, 2001), with political factors being a key driver behind this data manipulation(Chen et al., 2021). This raises an important question: Is the apparent political business cycle in China a result of genuine economic expansion, or is it merely a reflection of politically motivated data fabrication? In other words, do Chinese officials "cheat" to get promoted? To address this question, we employ the approach of Henderson et al. (2012) and use nighttime light data as a proxy for local economic activity. By comparing the official GDP growth rates with the growth rates derived from satellite imagery, we are able to estimate the extent of data manipulation. Using a panel dataset covering 330 Chinese prefecture-level cities from 1998 to 2020, we investigate whether there exists a political cycle of GDP overstatement that coincides with the National Party Congress (NCPC).

Our empirical analysis reveals a striking pattern: The discrepancy between official GDP growth rates and nighttime light-based growth rates exhibits a significant increase in the years of the NCPC, suggesting a political cycle of data manipulation. Furthermore, we find that while official data show a political business cycle with higher growth rates during NCPC years, the nighttime light data indicate the opposite - a significant decrease in economic activity during these periods. These findings suggest that the apparent political business cycle in China is largely driven by data falsification rather than genuine economic expansion. We term this phenomenon the "political GDP manipulation cycle."

This paper makes three key contributions to the literature. First, it sheds new light on the debate over whether China's political business cycle is primarily driven by local political events or national ones(Yu et al., 2015; Tsai, 2016; Xi et al., 2018; Tian and Tian, 2021; Zhou et al., 2013). By analyzing the timing of personnel changes at different levels of government, we provide strong evidence that the National Communist Party Congress is the key political event shaping local officials' behavior. Second, our findings uncover a political GDP manipulation cycle in China, which challenges the conventional wisdom about the country's political business cycle(Xi et al., 2018). By showing that the apparent economic fluctuations are largely driven by data falsification, our study highlights the crucial importance of verifying official statistics using alternative data sources. This has profound implications not only for understanding China's true economic performance but also for studying political business cycles in other countries where data reliability may be a concern(Shi and Svensson, 2006). Finally, our results underscore the need to account for political factors when assessing and predicting China's true economic performance(Clark et al., 2020).

The remainder of this paper is structured as follows. Section 2 reviews the related literature. Section 3 describes the data and methodology. Section 4 presents the empirical results. Section 5 conducts robustness checks. Section 6 explores heterogeneity in the political cycle of data manipulation. Section 7 concludes.

2 Literature Review

This paper involves research on two aspects: first, it examines the extent of manipulation in China's economic GDP data and tries to provide a reliable measurement of the manipulation; second, it studies the incentive mechanisms behind local officials' manipulation of GDP data.

2.1 GDP Manipulation in China

Over the past forty years, China's economy has grown rapidly, with the GDP size measured in RMB increasing by nearly 300 times. However, the GDP reported by local governments in China is often considered to be exaggerated, leading to widespread concerns about the reliability of GDP numbers. The leaders of provinces such as Liaoning, Inner Mongolia, and Tianjin have admitted to exaggerating their economic data for past years by 20 percents to 40 percents. Even the central government in Beijing often lacks confidence in the GDP figures reported by localities (Lyu et al., 2018). Although regulations have been enacted to strengthen the independence of local statistical work, in 2023, the provinces of Shanxi and Guizhou were still accused of GDP manipulation.

There is a substantial amount of quantitative evidence proving the widespread manipulation of GDP figures in China. These methods primarily utilize the inconsistencies between GDP figures and significant actual industrial indicators to expose GDP manipulation. One of the most famous examples is the former Premier Li Keqiang's use of the average of three economic indicators - electricity consumption, railway cargo volumes, and bank loans disbursed - to assess the actual economic performance of localities, known as the Keqiang Index (Clark et al., 2020). An earlier study by Meng and Wang (2000) analyzed China's GDP against 168 industries' outputs and key indicators like freight volume and energy use and concluded that the growth rates of China's GDP were exaggerated by between 0.5 percent and 2.2 percents during the periods 1978–1991 and 1992–1997, respectively. Ma et al. (2014) studied the discrepancies between China's national aggregate statistical values and the sum of provincial figures. After excluding factors such as internal trade, they found that the industrial sector is the major contributor to discrepancies.

However, several studies suggest that China's GDP data may not be significantly overstated. Mehrotra and Paakkonen (2011) used factor analysis with various macroeconomic indicators and found that the resulting factors accurately reflect GDP trends with only minor discrepancies. Similarly, Holz (2014) compared the digit distribution of GDP growth rates between China and the United States, identifying no notable disparities. This inconsistency in research conclusions demonstrates the need for more precise and reliable measures of GDP manipulation.

2.2 Political Incentives of GDP Manipulation

The reasons behind GDP manipulation are diverse, but the most crucial one stems from the promotion incentives of local officials. Institutional economists attribute China's economic miracle to a "Promotion Tournament" among local officials. In this tournament, GDP growth figures are given the highest weight in evaluations (Qian and Weingast, 1997; Zhou, 2007; Li et al., 2019). This incentive mechanism has led to a severe GDP frenzy. For example, in the "11th Five-Year Plan" in 2006, while the central government set the economic growth rate target at 7.5 percents, the local governments' average projected GDP growth was 10 percents, prompting the central government to urgently issue a directive for slowing down local GDP growth. Under such promotion incentives, local officials tend to use all available means, including falsifying data, to enhance the economic performance of their localities.

Some articles have already studied this. For example, Piotroski and Zhang (2014) found that local officials in China promote IPOs of domestically listed companies with political connections, and successful IPOs significantly increase the promotion probabilities of local officials. Another more recent study by Wang et al. (2020), based on 200 Chinese cities, also demonstrated that the promotions of city leaders are significantly positively correlated with abnormally rapid spatial expansion.

The incentive levels of local officials are also influenced by heterogeneous factors, among which tenure is an important factor. For example, Wang et al. (2021) found that first-term leaders, who are newly appointed after political turnover, attract more FDI inflows than continuing leaders. Another paper by Lyu et al. (2018) using regression discontinuity found that the likelihood of just meeting or beating GDP growth targets is stronger for governors with longer tenures. From this, it can be observed that local officials' efforts to boost GDP are strategic, and taking action at the right time can be expected to yield greater effects. Officials' tenures are often closely related to the Communist Party Congress (Shih et al., 2012). Although we have not found existing research that specifically studies the relationship between local Communist Party Congresses and GDP manipulation, this could be a meaningful gap in the research worth exploring.

3 Data and Methodology

3.1 How to measure Cheat GDP growth rate?

The most crucial variable in our article pertains to the measurement of data manipulation in China's economic growth. Currently, the predominant approach is to employ the method proposed by Henderson et al. (2012), which involves using nighttime light data to predict actual GDP growth. This methodology can estimate the real GDP growth figures, and it has been widely applied in studies investigating the falsification of economic growth data in China(Chen et al., 2021; Cai et al., 2022).

To be specific, we first collected the nighttime light data from the National Oceanic and Atmospheric Administration $NOAA$[1], and then processed the data to obtain the light growth rate. We then used the light growth rate to predict the actual GDP growth rate.

[1] The data could be get at `https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html#AVSLCFC`

$$\text{GDP growth}_i = \alpha_0 + \alpha_1 \text{Nightlight growth}_i + \delta_j + \varepsilon_i \tag{1}$$

The Eq.(1). show the regression we used to predict the actual GDP growth rate. The $GDPgrowth_i$ represent the real GDP growth rate from the China Urban Statistical Yearbook. The $Nightlightgrowth_i$ is the growth rate of nighttime light data, where the night light intensity is measured as the aggregate digital number (DN) within the city scaled by its area. The δ_i is the city fixed effect, and ε_i is the error term. Compared with Chen et al. (2021); Cai et al. (2022), we ignore the year fixed effect in the Eq.(1). This is because the political business cycle is highly correlated with the year fixed effect, so if we control the year fixed effect, we may lose the effect of the political business cycle in our baselien regression.

To mitigate light intensity measurement error, we follow Henderson et al. (2012) and combine the fitted values of the luminosity with the official GDP growth figures to arrive at an improved estimate of the real GDP growth. That is,

$$\text{True GDP growth} = \lambda \text{Official GDP growth} + (1-\lambda)\text{Light-estimated GDP growth} \tag{2}$$

The λ is the weight of the official GDP growth rate, and the $(1-\lambda)$ is the weight of the light-estimated GDP growth rate. And the λ is determined by the following equation.

$$\lambda = \operatorname*{argmin}_{\lambda} \text{Var}(\text{True GDP growth} - \text{Estimated True GDP growth}) \tag{3}$$

In Eq.(3), Var(True GDP growth) is the true real GDP growth rate, which is a value that we do not know but can be represent by an equation of nightlight growth rate. The Estimated True GDP growth is the estimated real GDP growth rate, which is a value we can get from Eq.(1). [2] After opitmitize Eq.(3)., we can get the Eq.(4)., which is the expression of the λ.

$$\lambda = \frac{\frac{\text{Var}(w)}{\text{Var}(w)+\text{Var}(z)}\text{Var}(z)\text{Var}(l) - \text{Cov}(z,l)^2}{\text{Var}(z)\text{Var}(l) - \text{Cov}(z,l)^2} \tag{4}$$

In Eq.(4)., the $\text{Var}(w)$ is the variance of the true GDP growth rate, which is unobservable. The $\text{Var}(z)$ is the variance of the official GDP growth rate, the $\text{Var}(l)$ is the variance of the nightlight growth rate. However, since we do not know the true GDP growth rate, we can not get the $\text{Var}(w)$. So Henderson et al. (2012) use the $\phi = \frac{\text{Var}(w)}{\text{Var}(w)+\text{Var}(z)}$ to include the $\text{Var}(w)$ into the another expression. The explanation of ϕ is the quality of the official GDP

[2] More details can be referred to the Henderson et al. (2012).

growth data. We can see that compared to countries with high-quality GDP data, countries with low-quality GDP data have much lower values of ϕ.

In this paper, the $\phi = 0.594$, which is a level used by Henderson et al. (2012) to esitmate the true GDP growth for countries with poor data, and this value was also used by Cai et al. (2022) when estimating the true GDP growth in China. After using $\phi = 0.594$, we can get the value of the $\lambda = 0.59$, which is similar to the calculated $\phi = 0.54$ in Chen et al. (2021).

After getting the λ, we can use the Eq.(2) to get the estimated true GDP growth rate. We the official GDP growth rate minus the estimated true GDP growth rate, we can get the fake GDP growth rate.

3.2 National Communist Party Congress and Provincial Communist Party Congress

In political business cycles theory Nordhaus (1975), the anticipation of an election is essential for officials to have the opportunity to engage in opportunistic behavior on the eve of elections, thereby boosting economic growth rates to win the preferences of voters. However, in China, this is not an easy task due to the elastic nature of the tenure of local officials. Although two laws issued by the central government [3] state that all officials at all levels of government and leadership of the party and government shall serve five-year terms, Xu (2011) and Geng et al. (2016) indicate that local officials usually serve three to four years. Figure 1 shows the tenure distribution of the mayor and party secretary in prefecture-level cities in our sample. It's apparent that most mayors and party secretaries serve for 2 to 4 years. Nonetheless, since the number of mayors and party secretaries whose tenure is 2 years is similar to the number of mayors and party secretaries whose tenure is 3 years and 4 years, it's also challenging for local officials to predict their own tenure with accuracy. Consequently, local officials may not be able to engage in opportunistic behavior to get a higher promotion probability at the end of their term. So it's challenging for local officials to predict their own tenure accurately.

However, does this imply that the absence of fixed terms in China negates the possibility of political business cycles? Not necessarily. Many scholars studying political business cycle in China consider the National Communist Party Congress(NCPC) and the Provincial Communist Party Congress(PCPC) as the timing of election to study on the political business cycle in China. This approach stems from the observation that a significant number of personnel changes among local officials are centered around the timings of the NCPC and

[3] *Law of the People's Congress of the People's Republic of China at All Levels and Local People's Governments at All Levels* promulgated in 2004 and the *Interim Provisions on the Term of Office of Leading Party and Government Cadres* promulgated in 2006

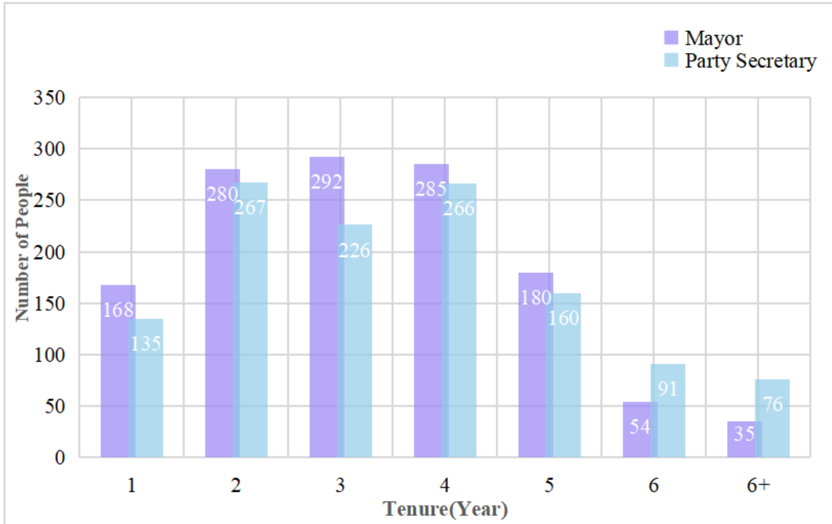

Figure 1: Tenure Distribution of Mayor and Party Secretary

PCPC. The NCPC determines the National Communist Party Committee, while the PCPC decides on the Provincial Communist Party Committee. Both of them are the highest authority in the corresponding administrative levels. Thus, the scheduling and rotation of a vast number of local officials typically occur around the time of these party congresses. Both the NCPC and PCPC have fixed timings, usually held every five years. The schedule for the NCPC is consistent nationwide, whereas the PCPC timings can vary by province, with 17 provinces holding their PCPC in the same year as the NCPC, typically between April and June. The remaining 13 provinces convene their local party congresses in the year preceding the NCPC, usually between October and December. The NCPC itself is generally held in November. Consequently, as timeline shown in Figure 2, the sequence of events typically starts with 13 provinces holding their PCPC at the end of the previous year, followed by the remaining 17 provinces conducting their PCPC in the mid of the following year, and finally, the NCPC at the end of that second year. In the study of China's political business cycles, provincial level phenomena are often analyzed with the NCPC as the electoral timing marker(Tsai, 2016; Mei et al., 2014). However, for municipal level political business cycle, whether to consider the provincial party congress or the municipal party congress as the electoral timing point remains a subject of debate among researchers. Xi et al. (2018) use the NCPC as the election timing point to study the political business cycle in China, while Zhou et al. (2013) and Tian and Tian (2021) use the PCPC as the election timing point to study the environmental political business cycle and the resource misallocation within political cycle in China.

Typically, scholars who use provincial communist party congresses as the election timing

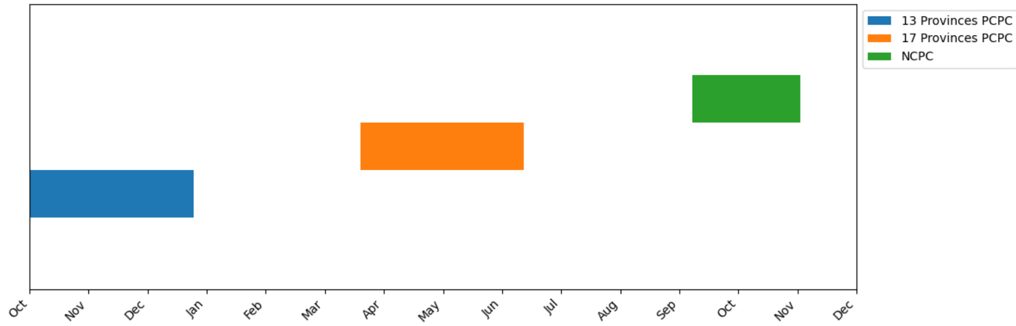

Figure 2: Tenure Distribution of Mayor and Party Secretary

point to study city-level political business cycle phenomena advocate two viewpoints to support their claim. The first point is that they believe a large number of changes in city-level officials occur around the time of the PCPC (Tian and Tian, 2021). As shown in Figure 3, a significant portion of prefecture-level city officials, whether they are mayors or party secretaries, are appointed in the year before or after the provincial party congress, with the highest number of political turnovers occurring in the year of the PCPC itself. Although PCPC do not directly determine the selection of city-level local officials, the most personnel changes occur in the vicinity of the provincial party congress. Therefore, they argue that provincial party congresses can be used as a time point that generates a large number of personnel changes, which motivates local officials to boost economic growth, thereby producing political business cycles. In contrast, although there are higher personnel changes before and after the NCPC, the number of personnel changes is lowest in the year of the NCPC. Thus, choosing PCPC as the election timing point in political business cycles seems to be more persuasive than selecting the NCPC. But is this really the case?

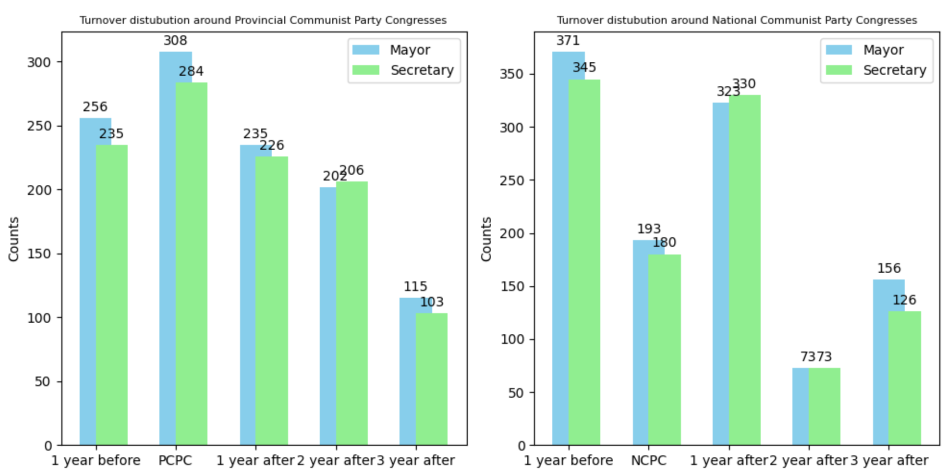

Figure 3: Turnover Distribution of Mayor and Party Secretary

To investigate this, we specifically counted the turnover times of officials from two groups of provinces that hold PCPC at different times. Group 1 consists of provinces that hold provincial party congresses in the year before the NCPC, while Group 2 includes provinces that hold PCPC in the same year as the NCPC. Table 1 presents the distribution of personnel changes based on the PCPC election cycle. We are surprised to find that although Group 1 indeed has the highest frequency of personnel changes in the year when the PCPC is held, the frequency of personnel changes in the year before and after the PCPC is not high. On the contrary, two years after the provincial party congress, another peak of personnel turnover emerges, with a number comparable to that of the PCPC year. This is clearly unreasonable because if we consider the number of official turnovers in a given year as the probability of an election occurring that year, according to the theory of political business cycles, if local officials in Group 1 only boost local economic growth in the PCPC year, they will obviously miss the opportunity to demonstrate their abilities before another major election. Moreover, if we consider the convening of the PCPC as the election timing point, we find that the distribution of personnel changes centered around the PCPC is asymmetric between Group 1 and Group 2. Specifically, for Group 2, the personnel changes peak in the years before, during, and after the PCPC, while the other two years are low points. In contrast, for Group 1, the personnel changes peak in the year of the PCPC and two years after the PCPC. Interestingly, Group 1 and Group 2 are almost evenly distributed across various regions in China, without any apparent inter-group differences(Zhou et al., 2013). Given this situation, why is the frequency of personnel changes asymmetric in their distribution around the PCPC between the two groups?

Table 1: The turnover disturbution of Mayor and Party Secretary around Provincial Communist Party Congress

	Mayor					Party Secretary				
	Before	PCPC	Post	Post_1	Post_2	Before	PCPC	Post	Post_1	Post_2
Total	255	305	238	201	117	226	288	229	204	107
Group 1	84	200	88	173	45	64	183	75	176	45
Group 2	171	105	150	28	72	162	105	154	28	62

If we consider the NCPC as the true central timing point for elections, this issue can be resolved. Table 2 presents the distribution of personnel changes based on the NCPC as the election timing point in the political business cycle. We observe that if the NCPC is considered the central election point of the entire political business cycle, the distributions of Group 1 and Group 2 become symmetrical. Both groups maintain a high frequency of personnel changes in the year before, during, and after the NCPC, while keeping a low frequency in the subsequent two years.

Table 2: The turnover disturbution of Mayor and Party Secretary around National Communist Party Congress

	Mayor					Party Secretary				
	Before	NCPC	Post	Post_1	Post_2	Before	NCPC	Post	Post_1	Post_2
Total	371	193	323	73	156	345	180	330	73	126
Group 1	200	88	173	45	84	183	75	176	45	64
Group 2	171	105	150	28	72	162	105	154	28	62

It is worth noting that the frequency of personnel changes is lowest in the year of the NCPC and highest in the year following the NCPC. This is because a large number of personnel changes are waiting for the convening of the NCPC to be adjusted. Therefore, the frequency of personnel changes is not high in the year when the NCPC is held. Moreover, since the NCPC is usually convened in October or November, the frequency of personnel changes throughout the entire year will not be very high. On the contrary, there may be a peak in the following year because the personnel change decisions made in the current year may be formally announced at the beginning of the next year(Shi and Xi, 2018).

Consequently, it is more reasonable to consider the NCPC as the true timing point for elections in China's political business cycle. Specifically, local officials will have the incentive to start boosting economic growth in the year before the NCPC and push it to the highest level during the NCPC year, in order to present the best economic performance to higher-level governments during the period surrounding the election.

The second point support for using PCPC as the election timing point is that it allows for the inclusion of year fixed effects. If the NCPC timing point is used as the political business cycle variable, since the NCPC timing variable is the same for every city, it would form perfect collinearity with the year fixed effects. In this case, it would be impossible to add year fixed effects. Consequently, the political business cycle effect would be confounded with the year fixed effects(Xi et al., 2018). However, if PCPC is used, since the convening times of the two groups of provinces are staggered, the perfect collinearity problem would not occur, making it possible to add year fixed effects. Moreover, in this case, the provinces that do not hold party congresses in the current year become the control group for those that do, transforming the original model into a DID model(Zhou et al., 2013). This provides a good source of identification for empirical research.

In two studies that investigate political business cycles using year fixed effects, the authors examine the resource misallocation effect(Zhou et al., 2013) and the environmental pollution effectTian and Tian (2021) under political business cycles, respectively. Although their research hypotheses rely on the assumption that political business cycles exist in China, they do not directly test for political business cycles after adding year fixed effects in their studies. However, we find that if year dummy variables are added to the empirical model using PCPC as the election timing point, as shown in Table 3, the coefficients capturing the political business cycle effect become insignificant. This suggests that political business cycles do not exist in China. This leads us to question whether using PCPC as the election timing point truly circumvents the bias in estimating the political business cycle effect caused by the multicollinearity problem.

Table 3: Political Business Cycle around PCPC using Year Fixed Effect

	GDP growth (1)	GDP growth (2)
Before	0.0735	
	(0.120)	
PCPC	-0.0579	
	(0.160)	
Post	0.135	
	(0.177)	
PBC		-0.00532
		(0.0273)
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	6503	6503
R-squared	0.4734	0.4733

Standard errors in parentheses are clustered at the city level.
* $p < 0.05$, *$p < 0.01$, *** $p < 0.001$

To examine this issue, we first assume that the political business cycle is indeed centered around the PCPC. Then, based on the political business cycle theory, we generate a set of data to test whether adding year fixed effects will cause multicollinearity to affect the estimation of the political business cycle variable. Specifically, we assume that the GDP growth rate in the year following the PCPC is 1 and increases year by year, reaching 5 in the year of the PCPC. Subsequently, we generate two groups of normal distributions based on the means and variances of the economic growth rates of Group 1 and Group 2. We then randomly sample according to whether the city belongs to Group 1 or Group 2 and sample the year fixed effects for each year from a normal distribution (0, 1). We then add the sampled residuals from a normal distribution (0, 1) and generate our simulated test data.

In Table 3, the simulated test data shows coefficients that are consistent with expectations and significant when year fixed effects are not added. However, when we add year fixed effects, we find that the estimated coefficients change significantly and start to become insignificant. This seems to confirm that even when using PCPC as the election timing point for the political business cycle, the political business cycle variables of the two staggered groups of provinces still generate multicollinearity problems with the year fixed effects, thereby affecting the estimation of the coefficients.

Table 4: Using Generated GDP Growth Data: PCPC Assumption

	Generate GDP Growth			
	(1)	(2)	(3)	(4)
Before	2.031***	0.462		
	(0.331)	(0.407)		
PCPC	3.215***	0.268		
	(0.308)	(0.475)		
Post	-0.110	-0.188		
	(0.284)	(0.402)		
PBC			0.834***	0.100
			(0.0729)	(0.106)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	7944	7944	7944	7944

Standard errors in parentheses are clustered at the city level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Furthermore, we conducted tests on the matrix combining the political business cycle variables, year dummy variables, and city dummy variables. First, we examined their condition numbers. Generally, matrices with larger condition numbers can experience significant changes in coefficients due to very small changes in the explained variables. If the condition number is extremely large and approaches positive infinity, the matrix may be very close to a singular matrix, indicating the presence of collinearity issues in the entire matrix. We separately examined the models using NCPC variables and PCPC variables as political business cycle variables. According to Table 5, we can find that except for the linear PBC model under the NCPC variable, which has a relatively small condition value, the condition values in other cases are extremely large, especially for the PCPC model, where they are almost very close to positive infinity. This raises doubts about whether using PCPC as a variable for the political cycle circumvents the multicollinearity problem.

Subsequently, we conducted a variance inflation factor (VIF) test. We found that the two empirical models of NCPC have VIFs greater than 10, and the empirical model of PCPC using the linear PBC model also has a VIF greater than 10, indicating the presence of multicollinearity issues. Although the model using PCPC dummy variables has a VIF less than 10, this result is based on the individual prediction of each PCPC dummy variable. If they are combined, it is still possible to obtain a result greater than 10, as shown by the previous condition values. Therefore, we believe that even when using PCPC as the election timing for studying political business cycles, the inclusion of year fixed effects will still lead to multicollinearity issues.

Based on the above two points, we argue that using NCPC as the election timing point is the appropriate approach for studying the phenomenon of political business cycles in China.

Table 5: Test for Mulicolinearity

	PCPC	PBC (PCPC)	NCPC	PBC (NCPC)
Condition number	1.69E+17	4.35E+18	1.1342E+15	283.3421347
VIF	3.18/4.67/4.60	11.11	5.40/2.22/5.25E+12	289.88

4 Empirical Models

To investigate the effect of the political cycle on the GDP manipulation, we refer to the econometric model in Xi et al. (2018), who studied on the political business cycle in China. The reason for this is that the political GDP data manipulation cycle and the political business cycle are highly correlated. Specifically, the purpose of both is to stimulate economic growth on the eve of elections to gain the preference of higher-level governments, thereby increasing the probability of promotion. However, in China, the political business cycle encompasses the political GDP data manipulation cycle because China's GDP data itself is of poor quality and contains overstatements caused by political factors. Therefore, China's political business cycle can be divided into two parts. One part is the real political business cycle, specifically, the genuine economic growth that occurs in the election year, which Chen et al. (2021) also referred to as the "Chasing effect." The other part is the fake political business cycle, where the economic growth in the election year is achieved through data manipulation, which is called 'Cheating Effect'. The political business cycle we observed earlier is a combination of these two parts. Consequently, we chose the model for studying China's political business cycle(Xi et al., 2018) as our benchmark model.

Eq(5). presents our benchmark model:

$$y_{i_t} = \beta_0 + \beta_1 PBC + \beta_5 X_{i_t} + \beta_6 Z_{i_t} + \delta_i + \epsilon_{i_t} \tag{5}$$

In Eq(5)., y_{i_t} is the cheated GDP growth rate of city i in year t. The PBC is the political business cycle variable, which is the main variable we are interested in. If this year is the year after the NCPC, the PBC is 1. Then the PBC will increasing year by year, reaching 5 in the year of the NCPC. The X_{i_t} is the vector of control variables, including the logrithm value of GDP, the population, the fixed asset investment, the number of employed persons and number of students enrolled in primary and regular secondary schools.

The Z_{i_t} is the vector of local officials' characteristics, including turnover, tenure, age, education level, and whether they were arrested for corruption now. The local official's characteristic contains mayor and party secretary's characteristics. The δ_i is the city fixed effect, and ϵ_{i_t} is the error term.

The endogeneity issue is relatively weak here because of the exogeneity of the political cycle variable. First, the reverse causality issue is weak here because the convening time of NCPC is given as exogenous and fixed. As a result, it's impossible for local officials to choose a date to hold the NCPC when their manipulated GDP growth rate is high. Second, there are a few omitted variables which are correlated with the convening of the NCPC and manipulated GDP growth at the same time. This is because the only reason for local officials to manipulate GDP growth is driven by their desire to win the preference of higher-level governments.

However, there are still some omitted variables in this model. To be included, they need to be highly correlated with the year of the NCPC convening and also related to officials' GDP growth manipulation behavior. One of the most influential variables is officials' turnover. This is because if an official leaves office in the year of the NCPC, there is no need for them to manipulate data to gain better promotion opportunities. Moreover, political turnover occurs at a high frequency around the NCPC. Therefore, we controlled for political turnover in the model and separately controlled for both mayors and party secretaries. Considering we don't include the year-fixed effect in the benchmark model, a potential missing variable problem caused by time-variant variable may bias our estimation. Therefore, a few control variables are added to the benchmark model to address this issue. All the control variables added in the model are referred to Chen et al. (2021) and Xi et al. (2018). The data of the control variables are from the China Urban Statistical Yearbook.

5 Empirical Results

Table 6 presents the results of our benchmark regression. In Column (1), we perform a regression only on the PBC variable using a fixed-effects model. We find that the coefficient of PBC is positive and statistically significant at the 1% confidence level. This implies that as the convening of the NCPC approaches, the cheated economic growth data will increase by 0.134 percentage points. Moreover, in the year when the NCPC is held, the fabricated economic growth data will be, on average, as high as 0.8 percentage points. Column (2), we control for a series of variables, including the logarithm of GDP, total population, fixed asset investment, year-end employment, and primary and secondary school enrollment. We discover that after controlling for these variables, the coefficient of PBC remains significantly positive and does not exhibit substantial differences compared to Column (1). Subsequently, in Column (3) and Column (4), we control for the personal characteristics of mayors and party secretaries, respectively, with a particular focus on their political turnover. Political turnover is an endogenous variable that influences the political GDP manipulation cycle. We observe that in Column (3) and Column (4), the coefficient of political turnover is negative and significant, which aligns with our expectations. When mayors and party secretaries are replaced in a given year, they no longer have the incentive to fabricate GDP data because their replacement positions have already been determined, thus exerting a negative impact on the fabricated economic growth. In Column (3) and Column (4), we find that PBC remains significantly positive and does not exhibit substantial differences compared to Column (1) and (2). These results suggest the existence of a political GDP manipulation cycle. Specifically, local officials, in order to increase their chances of promotion, engage in a certain degree of GDP data falsification prior to the convening of the NCPC, thereby creating the illusion of high economic growth and securing their advancement.

Table 6: Baseline Results: Political Cheating Cycle

	Fake GDP growth rate			
	(1)	(2)	(3)	(4)
PBC	0.134***	0.108***	0.108***	0.103***
	(0.0113)	(0.0164)	(0.0164)	(0.0167)
Mayor tenure			0.0566**	
			(0.0173)	
Mayor turnover			-0.196***	
			(0.0509)	
Secretary tenure				0.00425
				(0.0197)
Secretary turnover				-0.269***
				(0.0536)
City FE	Yes	Yes	Yes	Yes
Controlled variables	No	Yes	Yes	Yes
Mayor characteristics	No	No	Yes	No
Secretary characteristics	No	No	No	Yes
Observations	6601	3090	3062	3079
R-squared	0.0087	0.3213	0.3364	0.3245

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6 Robustness Checks

In the robustness tests, we employ three approaches to verify the robustness of our findings. First, we examine whether China exhibits a political business cycle and whether the growth rate of nighttime lights also fluctuates with the political cycle. Second, we test the competitiveness hypothesis using the convening of the PCPC as the election time point to observe whether we can obtain consistent and similar conclusions under the competitiveness hypothesis. Finally, we utilize XGBoost to re-predict China's local GDP growth rates using nighttime light data and investigate whether the cheated economic growth still fluctuates with the political cycle after the XGBoost prediction.

6.1 GDP Growth Rate and Light Growth Rate

The empirical results of the political GDP manipulation cycle are only reasonable if a political business cycle exists. Therefore, we must test whether a political business cycle is present in our sample. To do this, we replace the explanatory variable with China's officially reported GDP growth rate to observe whether China exhibits a political business cycle in our sample. Table 7 presents the results of our robustness tests. In Column (1), we observe that the coefficient of PBC is positive and statistically significant at the 1% confidence level. This is consistent with our expectations because only when the PBC coefficient is significantly positive, indicating that the economic growth rate is higher as the convening of the NCPC approaches, does it align with the predictions of the political business cycle theory. Moreover, this coefficient is close to the 0.351 estimated by Xi et al. (2018), which to a certain extent demonstrates the reasonableness of our coefficient estimation. In Column (2), we include control variables as in the benchmark regression, and the coefficient does not exhibit substantial differences. In Columns (3) and (4), we similarly control for the personal characteristics of local officials, with a particular focus on their turnover and tenure. This is because some literature studying China's political business cycles considers tenure as a core explanatory variable. However, we largely believe that tenure may measure the familiarity of local officials with the local economy, and the longer the tenure, the higher the familiarity, resulting in higher economic growth rates. Controlling for political turnover accounts for the decline in economic growth rates caused by officials leaving office, thereby avoiding biases in the political business cycle effect. We find that in Columns (3) and (4), both coefficients are significant and align with our expectations in terms of sign. Similarly, even after controlling for the personal characteristics of local officials, the coefficient of PBC remains significant, implying that China's political business cycle still exists within our sample.

Table 7: Robustness Check: Using GDP Growth Rate

	GDP growth rate			
	(1)	(2)	(3)	(4)
PBC	0.281***	0.242***	0.242***	0.235***
	(0.0272)	(0.0400)	(0.0399)	(0.0404)
Mayor tenure			0.153***	
			(0.0421)	
Mayor turnover			-0.417**	
			(0.126)	
Secret tenure				0.0198
				(0.0488)
Secret turnover				-0.576***
				(0.133)
City FE	Yes	Yes	Yes	Yes
Controlled variables	No	Yes	Yes	Yes
Mayor characteristics	No	No	Yes	No
Secretary characteristics	No	No	No	Yes
Observations	6618	3090	3062	3079
R-squared	0.0064	0.3184	0.3332	0.3243

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Furthermore, we observe whether the political cycle influences the growth rate of nighttime lights. We do not have a specific expectation regarding whether the growth rate of nighttime lights fluctuates with the political cycle. Specifically, if a positive cycle is observed, we can conclude that China's real political business cycle still exists. If there are no significant cyclical fluctuations, we can infer that China's political business cycle is primarily a phenomenon caused by data manipulation and has no actual relationship with economic growth. If a negative cycle is observed, it would be a rather interesting result, suggesting that China's actual political business cycle is reversed, with lower economic growth as the Party Congress approaches. Table 8 presents our regression results. We surprisingly find that the coefficient of PBC is negative and significant. Even after controlling for control variables and the characteristics of mayors and party secretaries, we still find that the growth rate is significantly negative. Specifically, as the convening of the NCPC approaches, we observe that the growth rate of nighttime lights decreases. On average, the closer to the year of the NCPC, the growth rate of nighttime lights decreases by 0.5%. This is a very surprising result. Since the linear PBC model is a strong assumption of the political economic cycle theory, stating that economic growth rates decrease after the election and gradually increase until the election year, it may not fully capture the specific details throughout the entire cycle. Therefore, we use the method of NCPC year dummy variables to further observe the fluctuations of nighttime light growth rates accompanying the political cycle in order to seek a possible explanation.

Table 8: Robustness Check: Using Light Growth Rate

	Light growth rate			
	(1)	(2)	(3)	(4)
PBC	-0.0101***	-0.00483***	-0.00526***	-0.00498***
	(0.00105)	(0.00123)	(0.00125)	(0.00123)
Mayor tenure			0.00350*	
			(0.00144)	
Mayor turnover			0.0149**	
			(0.00467)	
Secret tenure				0.00310**
				(0.00120)
Secret turnover				0.0181***
				(0.00473)
City FE	Yes	Yes	Yes	Yes
Controlled variables	No	Yes	Yes	Yes
Mayor characteristics	No	No	Yes	No
Secretary characteristics	No	No	No	Yes
Observations	6601	3090	3062	3079
R-squared	0.0127	0.0090	0.0169	0.0169

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The political business cycle theory actually suggests that politicians increase economic growth rates before elections and decrease them after elections to secure re-election, but it does not assume that the intermediate years necessarily follow a linear growth relationship. Therefore, we relax this assumption and use the dummy variables *Before*, *NCPC*, and *Post_1* in the regression to represent the political cycle, indicating whether it is the year before the NCPC, the year of the NCPC, or the year after the NCPC, respectively. In Table 9, we present the regression results using political cycle year dummy variables. Column (1) shows the regression results using the falsified economic growth rate as the dependent variable. We find that the reality does not satisfy the strong assumptions of the political business cycle. In the year before the NCPC, the fabricated GDP growth rate decreases. In the year of the NCPC, the fabricated GDP growth rate rises significantly, and then falls to the lowest point in the year after the NCPC. In Column (2), we use the officially reported GDP growth rate as the dependent variable. Similar to the political GDP manipulation cycle, we find that the GDP growth rate decreases in the year before the NCPC, rises substantially in the year of the NCPC, and then drops to the lowest point after the NCPC. In Column (3), we discover an even more interesting phenomenon. In the year before the NCPC, the growth rate of nighttime lights is significantly positive, implying that it is the highest economic growth rate in the cycle. However, it falls to the lowest point in the year of the NCPC and begins to recover in the following year. This series of interesting phenomena seems to suggest that local officials strive to make the GDP growth rate appear high in the year of the NCPC, but they do not actually boost the local economy in that year. Why is this the case? One possible explanation is that vigorously promoting economic growth in the year of the NCPC is not an optimal strategy. Although it can increase economic growth, the more active the economy is, the greater the likelihood of accidents or factors causing instability. Xu (2011) argues that in China's political selection system, the two main criteria for evaluating local officials are economic growth and social stability. To secure promotion, local officials must maintain a balance between the two. Although stimulating economic growth before the NCPC can lead to better economic performance, if accidents occur and affect social stability, it would be counterproductive. Not only would promotion be unattainable, but demotion might also be possible. One of the most widely studied types of accidents is coal mine accidents. Nie et al. (2013) and Shi and Xi (2018) both found that the number of fatalities in coal mine accidents begins to decrease before the NCPC and the annual local two sessions. This is because coal mine accidents themselves have an extremely negative impact on officials' promotions. Therefore, local officials strive to reduce the probability of these major negative events occurring before the NCPC. However, how can they promote economic growth while reducing the probability of social accidents before the NCPC? The answer lies in economic data manipulation. We speculate that China's local economic growth data is actually manipulated. If local officials only deliberately inflate economic growth in the year of the NCPC without understating it in other years, it may lead to an excessively large discrepancy and expose the issue of data falsification. Therefore, local officials are likely to stimulate economic growth in certain years but intentionally underreport the growth rate, while exaggerating economic growth and inflating the growth rate in the year of the NCPC. This approach avoids the problem of a significant gap between the reported GDP growth data and the real data. In subsequent research, we will further examine this perspective.

Table 9: Robustness Check: Using Year Dummy Model

	Fake GDP growth (1)	GDP growth (2)	Light growth (3)
Before	-0.205***	-0.361**	0.0331***
	(0.0484)	(0.121)	(0.00453)
NCPC	0.468***	0.873***	-0.0643***
	(0.0444)	(0.109)	(0.00372)
Post_1	-0.232***	-0.778***	-0.0509***
	(0.0486)	(0.117)	(0.00525)
City FE	Yes	Yes	Yes
Controlled variables	Yes	Yes	Yes
Secretary characteristics	Yes	Yes	No
Observations	3079	3079	3079
R-squared	0.3434	0.3354	0.1255

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.2 Competitive Hypothesis: Using PCPC as election timing point

Here, we test whether using the PCPC as the election time point in China's political business cycle might produce similar results. We perform regressions on the falsified GDP growth rate, officially reported GDP growth rate, and nighttime light growth rate, respectively. Table 10 presents our regression results. The first column shows the regression results for the falsified GDP growth rate, where we find that the coefficient is negative and insignificant. In Column (2), we regress the PBC variable on the official GDP growth rate and find that the coefficient is negative and also insignificant. However, in Column (3), when we regress the PBC variable on the nighttime light growth rate, we discover that the coefficient is positive and significant at the 1% confidence level. This is not an unexpected result because in Table 9, Column (3), we observed that the nighttime light growth rate is significantly positive in the year before the NCPC. Therefore, when using the PCPC as the election time point, it is equivalent to shifting the years forward by one year for some provinces. As a result, the PBC value of the NCPC becomes 1, while the original Before value becomes 5, thus fitting a positive political nighttime light cycle. This demonstrates that the linear PBC model is quite sensitive to the growth values at the beginning and end of the cycle. Although the coefficient in Column (3) is significantly positive, it cannot form a consistent hypothesis with the results in Column (1) and Column (2). In the absence of a political business cycle, there is no reason for a political nighttime light cycle to exist. The nighttime light cycle results we currently observe are more likely due to the backward shift of the values in the year before the NCPC in some provinces. Therefore, we can exclude the hypothesis that the PCPC is a key time point in the political business cycle.

Table 10: Robustness Check: Competitive Hypothesis

	Fake GDP growth (1)	GDP growth (2)	Light growth (3)
PBC(PCPC)	-0.0177	-0.0101	0.00788***
	(0.0174)	(0.0419)	(0.00121)
Secret tenure	0.0140	0.0423	0.00192
	(0.0198)	(0.0487)	(0.00118)
Secret turnover	-0.277***	-0.603***	0.0170***
	(0.0537)	(0.133)	(0.00479)
City FE	Yes	Yes	Yes
Controlled variables	Yes	Yes	Yes
Secretary characteristics	Yes	Yes	Yes
Observations	3079	3079	3079
R-squared	0.3209	0.3176	0.0237

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.3 Using XGBoost to predict true GDP growth

Next, we use XGBoost to predict the real GDP growth rate. Using traditional OLS to fit the real local GDP economic growth rate through nighttime light data can easily encounter the problem of large prediction accuracy errors, which may result in a significant discrepancy between the estimated real GDP economic growth rate and the official GDP growth rate. Therefore, following Chen et al. (2021), we employ a machine learning method called XGBoost to predict the real local GDP. We use the total annual nighttime light value, average nighttime light value, maximum nighttime light value, minimum nighttime light value, and provincial fixed effects to predict the real local GDP. Similarly, we omit year fixed effects to avoid XGBoost automatically learning the political business cycle, which would cause the predicted results to include the political business cycle effect. Finally, the real local GDP predicted by XGBoost has an average error of only 19% compared to the official data. Subsequently, we subtract the real GDP predicted by XGBoost from the officially reported GDP to calculate the fabricated GDP data. Table 11 presents our regression results. The first column shows the coefficient of the linear PBC model, which is positive but not significant. Then, we present the regression results using NCPC dummy variables. We find that the coefficient of the local falsified GDP in the year of the NCPC is significantly positive, indicating that even after using XGBoost to predict real economic data, we can still observe a political GDP manipulation cycle.

Table 11: Robustness Check: Using XGBoost to generate fake GDP growth

	Fake GDP (XGBoost)	
	(1)	(2)
PBC	5099.0	
	(35459.0)	
Before		102218.1
		(183663.6)
NCPC		587996.2***
		(162245.2)
Post		509189.8***
		(126648.9)
City FE	Yes	Yes
Controlled variables	Yes	Yes
Secretary characteristics	Yes	Yes
Observations	3077	3077
R-squared	0.2145	0.2206

Standard errors in parentheses are clustered at the city level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7 Heterogeneity Analysis

In this section, we conduct a heterogeneity analysis to observe whether the political GDP manipulation cycle varies with the personal characteristics of local officials. We mainly focus on the age and familiarity of mayors and party secretaries.

First, we consider the heterogeneity of local officials' age. Age plays a crucial role in GDP manipulation. According to Chen et al. (2021), if an official is younger, they are more eager to achieve and have good political prospects. If they are caught manipulating GDP data, it will ruin their political future. In other words, their opportunity cost of manipulating GDP data is higher compared to older officials. Therefore, the younger the local officials are, the less likely they are to exhibit a political GDP manipulation cycle. Consequently, we construct an interaction term between officials' age and PBC to observe this effect. In Columns (1) and (2) of Table 12, we observe that for both mayors and party secretaries, the coefficient of this interaction term is significantly positive. This implies that older officials are more likely to engage in political GDP manipulation cycle behavior.

To further investigate the heterogeneity in the political GDP manipulation cycle, we consider the length of time local officials have served in their current location before the NCPC. If an official has served in the locality for less than three years at the time of the NCPC, we consider their tenure to be short, and the familiarity value is set to 0. If they have served in the locality for more than three years at the time of the NCPC, we consider their tenure to be long, and the familiarity value is set to 1. We argue that if an official has served in the locality for a longer period and has a higher degree of familiarity with the area, they do not need to rely on the political GDP manipulation cycle to produce higher GDP growth rates in the year of the NCPC. Instead, they can actually promote GDP growth to achieve higher economic growth rates. However, if a local official is unfamiliar with the local situation before the NCPC, it is difficult for them to drive local GDP growth through their own abilities, and they are more likely to inflate the local GDP growth rate through the political GDP manipulation cycle. Columns (3) and (4) present our regression results. We find that for both mayors and party secretaries, the coefficients of the interaction term between familiarity and PBC are significantly negative. This result supports our hypothesis: if local officials have served for a shorter period before the NCPC and have limited knowledge of the local situation, they are more inclined to artificially create a high growth rate by manipulating GDP data to increase their chances of promotion. In contrast, officials who have served in the locality for many years before the NCPC and are very familiar with the local economic and social conditions are more capable of promoting economic growth through practical measures, thereby achieving genuine performance without relying on data falsification. Furthermore, we can explain this heterogeneous impact from the perspective of political incentives and accountability risks. For newly appointed local officials, due to the lack of sufficient time to leave substantial achievements, they may take risks and manipulate data to exaggerate their performance under the pressure of promotion. However, if such practices are exposed, it will seriously damage the officials' political prospects. Conversely, officials with longer tenures have more opportunities to steadily advance their work, accumulate real achievements, and are more concerned about their reputation, making them less willing to take the risk of falsifying data.

Table 12: Heterogeneity: Official's Age and Familiarity

	Fake GDP growth rate			
	(1) X=Mayor Age	(2) X=Secretary Age	(3) X=Mayor Familiarity	(4) Secretary Familiarity
PBC*X	0.00813*	0.0120**	-0.0675**	-0.0549
	(0.00505)	(0.00439)	(0.0361)	(0.0404)
X	-0.0700**	-0.0498*	0.435*	0.151
	(0.0247)	(0.0200)	(0.171)	(0.173)
PBC	-0.295	-0.521*	0.132***	0.126***
	(0.253)	(0.231)	(0.0209)	(0.0231)
Observations	3062	3079	3040	3057
City FE	Yes	Yes	Yes	Yes
Mayor characteristics	Yes	No	Yes	No
Secretary characteristics	No	Yes	No	Yes
R-squared	0.3297	0.3284	0.3247	0.3252

Standard errors in parentheses are clustered at the city level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

8 Conclusion

This paper investigates the existence of a political GDP manipulation cycle in China, shedding new light on the complex interplay between political incentives and economic performance. Using a novel approach that compares official GDP growth rates with growth rates derived from nighttime light satellite imagery, we uncover compelling evidence of a systematic pattern of data falsification tied to the political cycle.

Our findings suggest that local officials in China deliberately inflate reported GDP growth rates in the years leading up to the National Party Congress (NCPC) in order to enhance their promotion prospects.

Strikingly, while the official data exhibit a classic political business cycle pattern, with higher growth rates during NCPC years, the nighttime light data reveal the opposite trend - a significant decrease in economic activity during these periods. This stark discrepancy highlights the extent to which China's apparent economic fluctuations are driven by political manipulation rather than genuine growth.

Our study makes several important contributions to the literature on political business cycles and the reliability of official statistics. First, by providing strong evidence that China's political business cycle is primarily tied to the National Party Congress rather than local political events, we help to resolve an ongoing debate in the field. Second, our identification of a political GDP manipulation cycle challenges the conventional wisdom about the nature of China's economic fluctuations and underscores the critical importance of using alternative data sources to verify official figures. This finding has significant implications not only for understanding China's true economic performance but also for studying political business cycles in other contexts where data quality may be a concern. Finally, our analysis of heterogeneity in the political manipulation cycle sheds light on the role of officials' characteristics and incentives in shaping this behavior.

The results of this study have important implications for policymakers and researchers. For policymakers, our findings highlight the need for more robust checks and balances to ensure the integrity of official statistics and to mitigate the perverse incentives that drive data manipulation. And for researchers, our study opens up new avenues for investigating the complex interactions between political incentives, institutional factors, and economic outcomes in China and beyond.

Moreover, our finding that GDP growth rates decrease while nighttime light growth rates increase in the year before the NCPC is a puzzling phenomenon that warrants further attention. This observation raises the question of whether local officials strategically adjust reported GDP growth rates on a yearly basis to create the illusion of higher economic growth during NCPC years. Further research is needed to investigate this potential behavior and its implications for our understanding of the political GDP manipulation cycle.

While our paper makes significant strides in understanding the political GDP manipulation cycle in China, there is still much room for further research. Future studies could explore the mechanisms through which data falsification occurs, the consequences of this behavior for resource allocation and social welfare, and the potential for policy reforms to address this issue. Additionally, our findings raise important questions about the extent to which similar patterns of political manipulation may exist in other countries and contexts.

References

Aidt, T. S., Veiga, F. J., and Veiga, L. G. 2011. Election results and opportunistic policies: A new test of the rational political business cycle model. *Public Choice*, **148**(1):21–44.

Brender, A. and Drazen, A. 2005. Political budget cycles in new versus established democracies. *Journal of Monetary Economics*, **52**(7):1271–1295.

Cai, G., Li, X., Lin, B., and Luo, D. 2022. Gdp manipulation, political incentives, and earnings management. *Journal of Accounting and Public Policy*, **41**(5):106949.

Chen, S., Qiao, X., and Zhu, Z. 2021. Chasing or cheating? theory and evidence on china's gdp manipulation. *Journal of Economic Behavior & Organization*, **189**:657–671.

Clark, H., Pinkovskiy, M., and Sala-i Martin, X. 2020. China's gdp growth may be understated. *China Economic Review*, **62**:101243.

Dubois, E. 2016. Political business cycles 40 years after nordhaus. *Public Choice*, **166**(1):235–259.

Ferreira, A., Carvalho, J., and Pinho, F. 2013. Earnings management around zero: a motivation to local politician signalling competence. *Public Management Review*, **15**(5):657–686.

Geng, S., Pang, B., and Zhong, L. 2016. Local leadership tenure and government behavior patterns in china: The political economy of official tenure. *Economics Quarterly Journal*, **15**(3):893–916.

Guo, G. 2009. China's local political budget cycles. *American Journal of Political Science*, **53**(3):621–632.

Henderson, J. V., Storeygard, A., and Weil, D. N. 2012. Measuring economic growth from outer space. *American Economic Review*, **102**(2):994–1028.

Holz, C. A. 2014. The quality of china's gdp statistics. *China Economic Review*, **30**:309–338.

Kramer, G. H. 1971. Short-term fluctuations in us voting behavior, 1896–1964. *American Political Science Review*, **65**(1):131–143.

Li, X., Liu, C., Weng, X., and Zhou, L.-A. 2019. Target setting in tournaments: theory and evidence from china. *The Economic Journal*, **129**(623):2888–2915.

Lyu, C., Wang, K., Zhang, F., and Zhang, X. 2018. Gdp management to meet or beat growth targets. *Journal of Accounting and Economics*, **66**(1):318–338.

Ma, B., Song, G., Zhang, L., and Sonnenfeld, D. A. 2014. Explaining sectoral discrepancies between national and provincial statistics in china. *China Economic Review*, **30**:353–369.

Mehrotra, A. and Paakkonen, J. 2011. Comparing china's gdp statistics with coincident indicators. *Journal of Comparative Economics*, **39**(3):406–411.

Mei, D., Wang, Z., and Lei, W. 2014. Party congress held, changes in supervision and china's economic fluctuations. *Economic Research Journal*, **49**(3):47–61.

Meng, L. and Wang, X. 2000. An evaluation of the reliability of china's statistics on economic growth. *Economic Research Journal*, **10**:3–13.

Nie, H., Jiang, M., and Wang, X. 2013. The impact of political cycle: Evidence from coalmine accidents in china. *Journal of Comparative Economics*, **41**(4):995–1011.

Nordhaus, W. D. 1975. The political business cycle. *The Review of Economic Studies*, **42**(2):169–190.

Piotroski, J. D. and Zhang, T. 2014. Politicians and the ipo decision: The impact of impending political promotions on ipo activity in china. *Journal of Financial Economics*, **111**(1):111–136.

Qian, Y. and Weingast, B. R. 1997. Federalism as a commitment to preserving market incentives. *Journal of Economic perspectives*, **11**(4):83–92.

Rawski, T. G. 2001. What is happening to china's gdp statistics? *China Economic Review*, **12**(4):347–354.

Rogoff, K. and Sibert, A. 1988. Elections and macroeconomic policy cycles. *The Review of Economic Studies*, **55**(1):1–16.

Shi, M. and Svensson, J. 2006. Political budget cycles: Do they differ across countries and why? *Journal of Public Economics*, **90**(8-9):1367–1389.

Shi, X. and Xi, T. 2018. Race to safety: Political competition, neighborhood effects, and coal mine deaths in china. *Journal of Development Economics*, **131**:79–95.

Shih, V., Adolph, C., and Liu, M. 2012. Getting ahead in the communist party: explaining the advancement of central committee members in china. *American Political Science Review*, **106**(1):166–187.

Tian, Z. and Tian, Y. 2021. Political incentives, party congress, and pollution cycle: empirical evidence from china. *Environment and Development Economics*, **26**(2):188–204.

Tsai, P.-H. 2016. Fiscal incentives and political budget cycles in china. *International Tax and Public Finance*, **23**(6):1030–1073.

Wang, D., Zhu, Z., Chen, S., and Luo, X. R. 2021. Running out of steam? a political incentive perspective of fdi inflows in china. *Journal of International Business Studies*, **52**:692–717.

Wang, Z., Zhang, Q., and Zhou, L.-A. 2020. Career incentives of city leaders and urban spatial expansion in china. *Review of Economics and Statistics*, **102**(5):897–911.

Xi, T., Yao, Y., and Zhang, M. 2018. Capability and opportunism: Evidence from city officials in china. *Journal of Comparative Economics*, **46**(4):1046–1061.

Xu, C. 2011. The fundamental institutions of china's reforms and development. *Journal of Economic Literature*, **49**(4):1076–1151.

Yu, J., Xiao, J., and Gong, L. 2015. Political cycle and local government's land transfer behavior. *Economic Research Journal*, **2**:88–102.

Zhang, J. and Gao, Y. 2007. Official tenure, remote exchange and economic growth. *Economic Research Journal*, **11**:91–103.

Zhou, L.-A. 2007. Governing china's local officials: An analysis of promotion tournament model. *Economic Research Journal*, **7**:36–50.

Zhou, L.-A., Zhao, Y., and Li, L. 2013. Resource misallocation and political cycles. *Financial Research Journal*, **3**.

Listing 1: Code for the Paper

```
# Package Loading
import pandas as pd
import numpy as np
import scipy.stats as stats
from linearmodels.panel import PooledOLS, PanelOLS


# Data Loading
dataset = pd.read_csv("dataset.csv")
dataset.columns


# Macro Definition
ncpc_pbc = ["nc_pbc"]
pbc = ["pbc"]
ncpc = ["ncpc_before", "ncpc", "ncpc_post"]
pcpc = ["before", "pcpc", "post"]
control = ["employment", "investment", "education", "ln_gdp", "ln_population"]
mayor_char = [
    "mayor_tenure", "mayor_turnover", "mayor_age",
    "mayor_education", "mayor_corruption",
]
secret_chat = [
    "secret_tenure", "secret_turnover", "secret_age",
    "secret_education", "secret_corruption",
]

ncpc_control = ncpc + control
pcpc_control = pcpc + control
ncpc_pbc_control = ncpc_pbc + control
pbc_control = pbc + control

ncpc_mayor = ncpc_control + mayor_char
ncpc_pbc_mayor = ncpc_pbc_control + mayor_char
pcpc_mayor = pcpc_control + mayor_char
pcpc_pbc_mayor = pbc_control + mayor_char
```

```
ncpc_secret = ncpc_control + secret_chat
ncpc_pbc_secret = ncpc_pbc_control + secret_chat
pcpc_secret = pcpc_control + secret_chat
pcpc_pbc_secret = pbc_control + secret_chat


def drop_na_columns(dataset, col_a, col_b):
    full_dataset = pd.concat(
        [dataset[["year", "city"]], dataset[col_a], dataset[col_b]],
            axis=1
    )
    full_dataset = full_dataset.dropna()
    return full_dataset


# Baseline Results

## Table06 "Baseline Results: Political Cheating Cycle"
fake_gdp = ["fake_gdp_growth"]

dataset_1 = drop_na_columns(dataset, fake_gdp, ncpc_pbc)
dataset_1.set_index(["city", "year"], inplace=True)
model_1 = PanelOLS(dataset_1[fake_gdp], dataset_1[ncpc_pbc],
   entity_effects=True)
result_1 = model_1.fit(cov_type="clustered", cluster_entity=True)
result_1.summary

dataset_2 = drop_na_columns(dataset, fake_gdp, ncpc_pbc_control)
dataset_2.set_index(["city", "year"], inplace=True)
model_2 = PanelOLS(dataset_2[fake_gdp], dataset_2[ncpc_pbc_control],
    entity_effects=True)
result_2 = model_2.fit(cov_type="clustered", cluster_entity=True)
result_2.summary

dataset_3 = drop_na_columns(dataset, fake_gdp, ncpc_pbc_mayor)
dataset_3.set_index(["city", "year"], inplace=True)
model_3 = PanelOLS(dataset_3[fake_gdp], dataset_3[ncpc_pbc_control],
```

```
    entity_effects=True)
result_3 = model_3.fit(cov_type="clustered", cluster_entity=True)
result_3.summary

dataset_4 = drop_na_columns(dataset, fake_gdp, ncpc_pbc_secret)
dataset_4.set_index(["city", "year"], inplace=True)
model_4 = PanelOLS(dataset_4[fake_gdp], dataset_4[ncpc_pbc_control],
    entity_effects=True)
result_4 = model_4.fit(cov_type="clustered", cluster_entity=True)
result_4.summary


# Robustness Checks

## Table07 "Using GDP Growth Rate"
gdp_growth = ["gdp_growth"]

dataset_1 = drop_na_columns(dataset, gdp_growth, ncpc_pbc)
dataset_1.set_index(["city", "year"], inplace=True)
model_1 = PanelOLS(dataset_1[gdp_growth], dataset_1[ncpc_pbc],
   entity_effects=True)
result_1 = model_1.fit(cov_type="clustered", cluster_entity=True)
result_1.summary

dataset_2 = drop_na_columns(dataset, gdp_growth, ncpc_pbc_control)
dataset_2.set_index(["city", "year"], inplace=True)
model_2 = PanelOLS(dataset_2[gdp_growth], dataset_2[ncpc_pbc_control
   ], entity_effects=True)
result_2 = model_2.fit(cov_type="clustered", cluster_entity=True)
result_2.summary

dataset_3 = drop_na_columns(dataset, gdp_growth, ncpc_pbc_mayor)
dataset_3.set_index(["city", "year"], inplace=True)
model_3 = PanelOLS(dataset_3[gdp_growth], dataset_3[ncpc_pbc_mayor],
    entity_effects=True)
result_3 = model_3.fit(cov_type="clustered", cluster_entity=True)
result_3.summary

```

```
dataset_4 = drop_na_columns(dataset, gdp_growth, ncpc_pbc_secret)
dataset_4.set_index(["city", "year"], inplace=True)
model_4 = PanelOLS(dataset_4[gdp_growth], dataset_4[ncpc_pbc_secret
    ], entity_effects=True)
result_4 = model_4.fit(cov_type="clustered", cluster_entity=True)
result_4.summary


## Table08 "Using Light Growth Rate"
light_growth = ["light_growth_1"]

dataset_1 = drop_na_columns(dataset, light_growth, ncpc_pbc)
dataset_1.set_index(["city", "year"], inplace=True)
model_1 = PanelOLS(dataset_1[light_growth], dataset_1[ncpc_pbc],
    entity_effects=True)
result_1 = model_1.fit(cov_type="clustered", cluster_entity=True)
result_1.summary

dataset_2 = drop_na_columns(dataset, light_growth, ncpc_pbc_control)
dataset_2.set_index(["city", "year"], inplace=True)
model_2 = PanelOLS(dataset_2[light_growth], dataset_2[
    ncpc_pbc_control], entity_effects=True)
result_2 = model_2.fit(cov_type="clustered", cluster_entity=True)
result_2.summary

dataset_3 = drop_na_columns(dataset, light_growth, ncpc_pbc_mayor)
dataset_3.set_index(["city", "year"], inplace=True)
model_3 = PanelOLS(dataset_3[light_growth], dataset_3[ncpc_pbc_mayor
    ], entity_effects=True)
result_3 = model_3.fit(cov_type="clustered", cluster_entity=True)
result_3.summary

dataset_4 = drop_na_columns(dataset, light_growth, ncpc_pbc_secret)
dataset_4.set_index(["city", "year"], inplace=True)
model_4 = PanelOLS(dataset_4[light_growth], dataset_4[
    ncpc_pbc_secret], entity_effects=True)
result_4 = model_1.fit(cov_type="clustered", cluster_entity=True)
result_4.summary
```

```
## Table09 "Using Year Dummy Model"
dataset_1 = drop_na_columns(dataset, fake_gdp, ncpc_secret)
dataset_1.set_index(["city", "year"], inplace=True)
model_1 = PanelOLS(dataset_1[fake_gdp], dataset_1[ncpc_secret],
    entity_effects=True)
result_1 = model_1.fit(cov_type="clustered", cluster_entity=True)
result_1.summary

dataset_2 = drop_na_columns(dataset, gdp_growth, ncpc_secret)
dataset_2.set_index(["city", "year"], inplace=True)
model_2 = PanelOLS(dataset_2[gdp_growth], dataset_2[ncpc_secret],
    entity_effects=True)
result_2 = model_2.fit(cov_type="clustered", cluster_entity=True)
result_2.summary

dataset_3 = drop_na_columns(dataset, light_growth, ncpc_secret)
dataset_3.set_index(["city", "year"], inplace=True)
model_3 = PanelOLS(dataset_3[light_growth], dataset_3[ncpc_secret],
    entity_effects=True)
result_3 = model_3.fit(cov_type="clustered", cluster_entity=True)
result_3.summary


## Table10 "Competitive Hypothesis"
dataset_1 = drop_na_columns(dataset, fake_gdp, pcpc_pbc_secret)
dataset_1.set_index(["city", "year"], inplace=True)
model_1 = PanelOLS(dataset_1[fake_gdp], dataset_1[pcpc_pbc_secret],
    entity_effects=True)
result_1 = model_1.fit(cov_type="clustered", cluster_entity=True)
result_1.summary

dataset_2 = drop_na_columns(dataset, gdp_growth, pcpc_pbc_secret)
dataset_2.set_index(["city", "year"], inplace=True)
model_2 = PanelOLS(dataset_2[gdp_growth], dataset_2[pcpc_pbc_secret
    ], entity_effects=True)
result_2 = model_2.fit(cov_type="clustered", cluster_entity=True)
```

```
result_2.summary

dataset_3 = drop_na_columns(dataset, light_growth, pcpc_pbc_secret)
dataset_3.set_index(["city", "year"], inplace=True)
model_3 = PanelOLS(dataset_3[light_growth], dataset_3[
    pcpc_pbc_secret], entity_effects=True)
result_3 = model_3.fit(cov_type="clustered", cluster_entity=True)
result_3.summary


## Table11 "Using XGBoost to Generate Fake GDP Growth"
xg_boost = ["fake_xg"]

dataset_1 = drop_na_columns(dataset, xg_boost, ncpc_pbc_secret)
dataset_1.set_index(["city", "year"], inplace=True)
model_1 = PanelOLS(dataset_1[xg_boost], dataset_1[ncpc_pbc_secret],
    entity_effects=True)
result_1 = model_1.fit(cov_type="clustered", cluster_entity=True)
result_1.summary

dataset_2 = drop_na_columns(dataset, xg_boost, ncpc_secret)
dataset_2.set_index(["city", "year"], inplace=True)
model_2 = PanelOLS(dataset_2[xg_boost], dataset_2[ncpc_secret],
    entity_effects=True)
result_2 = model_2.fit(cov_type="clustered", cluster_entity=True)
result_2.summary
```