GDP Misreporting and Economic Convergence

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Abstract

I use nighttime lights and electricity consumption to detect GDP misreporting and reassess economic convergence. In China, official data imply an annual convergence rate of 2.1% after the 2000s, whereas the constructed measure implies 1.7%. After the 2002 tax reform, the central government expanded redistribution from high- to low-income regions, increasing the cost of overreporting and lowering GDP overstatement by rich provinces. This pattern accounts for artificially rapid convergence in official statistics. Extending the analysis globally, I find stronger evidence of convergence in Africa and the Americas once growth is better measured.

Key words: Economic Convergence, GDP Misreporting, Nighttime Light, Electricity Consumption, Regional Redistribution, Political Incentives.

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1 Introduction

During the past two decades, China has experienced rapid regional economic convergence. The variance of log provincial GDP per capita fell from 0.27 in 2000 to 0.15 in

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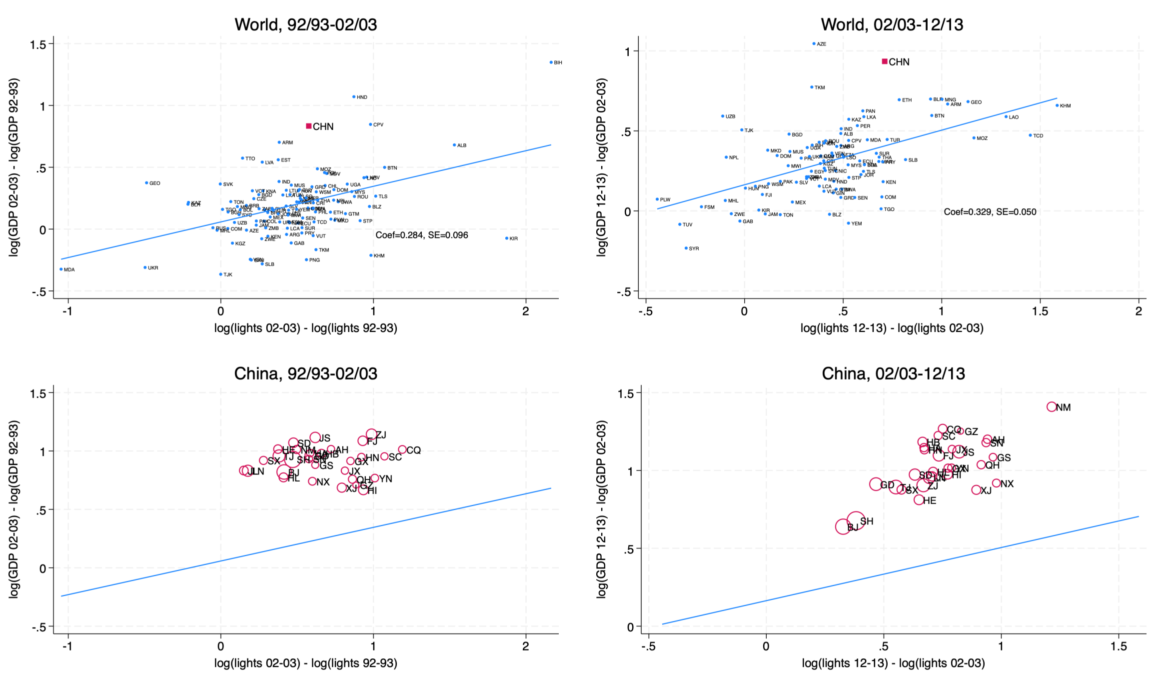
2020. This stylized fact, however, is based on China's official GDP statistics, whose credibility is frequently questioned. This raises a fundamental concern: is the observed convergence a genuine economic transition or an artifact of statistical manipulation?

To address this question, I use nighttime lights to detect GDP misreporting in China. In the top panel of Figure 1, China appears as an outlier with relatively high reported GDP growth but low nighttime light growth, indicating substantial overreporting of official GDP figures. More strikingly, the bottom panel shows that provincial patterns of overreporting changed sharply after 2002. Before 2002, misreporting appears broadly similar across provinces. After 2002, poorer provinces lie systematically farther above the cross-country fitted line than richer provinces, suggesting that GDP overreporting became more concentrated in initially poor regions. This pattern suggests that part of the observed regional convergence may be statistical.

Figure 1: GDP Growth and Nighttime Light Growth: World and Chinese Provinces



Note: These figures plot GDP growth against nighttime light growth from 1992/1993 to 2002/2003 (left) and from 2002/2003 to 2012/2013 (right). The y-axis shows changes in log GDP, and the x-axis shows changes in log nighttime light. The world sample includes low- and middle-income countries with good-quality official GDP data. The solid line is the fitted line estimated from the global sample. Each dot in the top panel represents a country; each dot in the bottom panel represents a Chinese province. In the bottom panel, dot size is proportional to initial GDP per capita.

Motivated by these facts, this paper has two goals. First, following the framework developed by Henderson, Storeygard and Weil (2012) (HSW hereafter), I detect GDP misreporting using nighttime lights and electricity consumption. The constructed measure helps reassess regional convergence in China and can also be applied to global data. Second, I relate the changing pattern of GDP misreporting in China to the country's regional redistribution system and provide a theory of the fiscal cost of overreporting economic performance.

I begin by developing a parsimonious model of local GDP overreporting. The framework builds on the Mandarin growth model of Song and Xiong (2023), in which local officials overreport regional output to improve their promotion prospects. I extend this framework by incorporating China's regional redistribution system. While local officials have incentives to exaggerate economic performance, overreporting becomes costly when reported output affects fiscal payments to the central government. As the central government expanded redistribution from rich to poor regions, this fiscal cost increased more for high-output regions. The model therefore predicts that, under a progressive redistribution system, richer regions should reduce overreporting relative to poorer regions. This mechanism generates a statistical component of observed convergence in official GDP data.

Motivated by the theoretical framework, I use nighttime lights and electricity consumption to detect GDP misreporting in official statistics. HSW infer true economic growth by combining official GDP growth with light-predicted growth. Their framework, however, is underidentified: the available moments are insufficient to recover the optimal weights without additional assumptions. Building on the three-signal framework of Civelli, Gaduh and Yousuf (2024), I introduce electricity consumption as an additional measure of economic activity. Electricity use is tightly linked to production and is plausibly less susceptible to manipulation than GDP statistics. A 1% increase in electricity consumption growth is associated with a 0.24%–0.27% increase in GDP per capita in the global sample. In China, electricity data show a similar pattern that poorer regions appear to overreport GDP growth more than richer regions after 2002. Under the maintained measurement-error assumptions, adding this third signal provides enough moments to recover the parameters of the measurement system and to compute the optimal weights on each indicator. My estimates assign larger weights to nighttime lights and electricity consumption than to official GDP. This suggests that the two physical indicators provide useful information beyond official statistics and help construct a more precise measure of economic growth.

Applying this framework to Chinese provincial data, I find that official GDP implies an annual β-convergence rate of 2.1%, whereas the optimally combined measure implies a rate of 1.7%. Thus, about 20% of the observed convergence is attributable to GDP misreporting. I interpret this pattern through the fiscal-cost channel highlighted by the model. After the 2002 tax reform, the central government expanded redistribution from rich to poor regions, so overreporting GDP became associated with higher payments to the central government and fewer transfers received. As redistribution became increasingly progressive, rich provinces faced higher marginal tax rates and became less willing to inflate growth. Consistent with this mechanism, rich provinces reduced overstatement of economic performance relative to poor provinces after 2002, accounting for artificially rapid convergence in official data. I show that this interpretation is supported by additional validation exercises: the constructed measure of overreporting is related to local officials' promotion incentives, is not explained by informal-sector size or industrial structure, and remains robust to top-coding-corrected nighttime lights and heterogeneous elasticities across income groups.

Extending the analysis globally, I find that, although much of the literature documents limited evidence of global convergence, GDP mismeasurement may bias this conclusion. In low-income economies with weak statistical capacity and large informal sectors, official GDP figures may understate true economic growth. By contrast, autocratic regimes may overreport GDP growth. Using GDP growth adjusted by nighttime lights and electricity consumption, I document stronger regional convergence in Africa and the Americas, and slower convergence in Asia and Europe.

Related Literature. This paper contributes to several strands of literature. First, it contributes to the literature that uses nighttime lights to measure economic activity, pioneered by Chen and Nordhaus (2011) and Henderson, Storeygard and Weil (2012).[1]

[1] Subsequent studies using nighttime lights to measure economic activity include, among others, Pinkovskiy and Sala-i Martin (2016); Chodorow-Reich et al. (2020); Gibson et al. (2021); Chen, Qiao and Zhu (2021). Related work has used other data sources to assess mismeasurement in official GDP statistics, including value-added tax receipts (Chen et al., 2019), Engel curves (Nakamura, Steinsson

A central challenge in this literature is identification. In the original HSW framework, the available observables provide insufficient moments to recover the unknown parameters. Hu and Yao (2022) address this problem by using auxiliary information on statistical capacity and geographic location to infer the distribution of measurement error. Civelli, Gaduh and Yousuf (2024) instead develop a three-signal framework by introducing urban land cover as an additional measure of economic activity. I build on this approach but use electricity consumption as the third signal. This choice is useful for my setting for two reasons. First, electricity use is closely linked to production and is plausibly less directly affected by local officials' incentives to report headline GDP. For this reason, electricity consumption has been used as an alternative indicator of Chinese economic activity, most notably in the Li Keqiang index and in related studies such as Wallace (2016) and Clark, Pinkovskiy and Sala-i Martin (2020). Second, unlike land cover, electricity consumption is not derived from satellite imagery and is therefore less likely to share the same remote-sensing measurement errors as nighttime lights. Under the maintained measurement-error assumptions, electricity consumption provides additional identifying variation and allows me to obtain sharper estimates of GDP growth.

This paper also contributes to the literature on the mechanisms underlying GDP misreporting. Magee and Doces (2015) document a positive correlation between GDP growth and autocracy after controlling for nighttime light growth, while Martinez (2022) finds that the elasticity of nighttime light growth with respect to official GDP growth differs between democratic and autocratic regimes. These findings provide evidence that autocracies are more likely to overstate economic performance. Within China, previous work links GDP overstatement to local officials' promotion incentives (Song and Xiong, 2023; Gong, Shen and Chen, 2025). In particular, Zeng and Zhou (2024) find that mayors' promotion incentives increase official GDP growth but have no effect on nighttime light growth. While the incentives to overreport GDP are well studied, the fiscal cost of doing so has received less attention. I contribute to this literature by highlighting the financial cost of overreporting created by China's regional redistribution system.

and Liu, 2016), and coincident indicators (Mehrotra and Pääkkönen, 2011).

This paper also relates to the literature on economic convergence. Existing studies find limited evidence of global economic convergence (Barro, 1991; Barro and Sala-i Martin, 1992; Gennaioli et al., 2014; Jones, 2016). More recently, Patel, Sandefur and Subramanian (2021) and Kremer, Willis and You (2022) document evidence of convergence since the 2000s. Evidence on economic convergence in China is mixed. For example, Jian, Sachs and Warner (1996) and Kanbur and Zhang (2005) document economic divergence after 1990 and relate it to coastal-biased growth. More recently, Fleisher, Li and Zhao (2010) emphasize human capital accumulation in less-developed regions as a key force for reducing regional inequality, while Brandt, Kambourov and Storesletten (2025) highlight changes in entry barriers as an explanation for economic convergence. However, Cheong and Wu (2013) find high persistence in the income distribution across spatial groupings, and Andersson, Edgerton and Opper (2013) find that Chinese provinces diverge in the short run but cluster into two converging growth clubs in the long run.

This mixed evidence underscores the need for better-measured growth data. With the increasing availability of nighttime light data, a growing literature uses luminosity to measure regional income and inequality when official statistics are unavailable or unreliable. For example, Alesina, Michalopoulos and Papaioannou (2016) use nighttime luminosity to recover ethnic inequality and study its economic and geographic origins. Lessmann and Seidel (2017) use nighttime lights to measure regional inequality within countries and find that about 70% of countries experience σ-convergence. My paper uses nighttime light data to highlight a novel possibility: observed convergence in official statistics may reflect not only real economic dynamics, but also systematic mismeasurement. To the best of my knowledge, this is the first paper to link the appearance of economic convergence directly to measurement error in official statistics.

The remainder of the paper is organized as follows. Section 2 reviews the political tournament and the regional redistribution system in China. Section 3 presents a heuristic model that motivates the empirical design. Section 4 presents the methodology used to construct the measure of GDP growth. Section 5 reports the main empirical findings on GDP misreporting and economic convergence in China. Section 6 performs several robustness checks. Section 7 concludes.

2 Institutional Background

2.1 Political Tournament

Local officials' promotion prospects are closely tied to local economic performance in China. A growing body of literature documents this link. For instance, Maskin, Qian and Xu (2000) find a significant positive correlation between changes in relative economic performance and changes in political rank. Li and Zhou (2005) and Xu (2011) show that stronger economic performance increases the likelihood of promotion for provincial leaders.

The tournament-style promotion system has been an important driver of economic growth in China. In pursuit of promotion, local governors have incentives to improve economic performance by building regional infrastructure, attracting investment, fostering a business-friendly environment, and encouraging innovation. Meanwhile, high-ability officials who perform well are more likely to be promoted to more important positions and to exert greater effort in future roles.

However, the political tournament also has unintended consequences. An exclusive focus on short-term GDP growth can distort policy priorities, leading to overinvestment in infrastructure, rising government debt, local protectionism, and environmental pollution (Zheng and Kahn, 2013; Fang, Li and Wu, 2022; Song and Xiong, 2023). In addition, local governments may conceal bad news and distort official statistics to improve the appearance of performance (Wallace, 2016). Since local officials are rewarded for meeting growth targets, local governments have incentives to inflate GDP figures. Because the national accounts rely heavily on data collected by local statistical bureaus, such behavior can contribute to overstatement in China's official GDP data (Chen et al., 2019).

2.2 Regional Redistribution

China operates a centralized fiscal redistribution system that reallocates local government revenue from developed to less developed regions. In 1994, the central government began collecting all excise taxes and 75% of value-added taxes from local governments. In 2002, it also began claiming 50% of personal and corporate income taxes. This share increased to 60% in 2003. At the same time, the central government committed to transferring all collected income taxes to less developed regions. Around 2010, central taxes amounted to about 10% of GDP, while transfers to local governments amounted to about 8% of GDP. More importantly, these transfers were disproportionately directed toward poor regions.

To track the evolution of the redistribution system, I model the cross-regional redistribution of fiscal revenue as a progressive tax on local governments and use the log-linear tax schedule in Heathcote, Storesletten and Violante (2017) to measure the degree of progressivity. Let Y denote GDP per capita, and define $\tilde{Y}$ as GDP per capita net of central taxes plus transfers from the central government. Then the net tax contributed to the central government is given by:

$$T(Y) = Y - \tilde{Y} = Y - \lambda Y^{1-\phi} \tag{1}$$

where ϕ controls the degree of progressivity and λ controls the average level of taxes. The marginal tax rate (MTR) is then:

$$MTR = T'(Y) = 1 - \lambda(1-\phi)Y^{-\phi} \tag{2}$$

which is increasing in Y when $\phi > 0$. Since $\tilde{Y} = \lambda Y^{1-\phi}$, ϕ can be estimated from the following regression:

$$\log \tilde{Y}_{it} = \log \lambda + (1-\phi)\log Y_{it} + \eta_{it} \tag{3}$$

I estimate ϕ for each year using regression (3) and report the results in Figure A1. Estimated progressivity increased markedly from about 0.1 around 2002 to 0.3 around 2015.

To illustrate the implications for the MTR, I use Equation (2) to compute the theoretical MTR in Figure A2. In 1997, the MTR ranged from 0.02 to 0.14 across provinces, with limited variation by GDP level. In 2013, as progressivity increased, the MTR rose to a range of 0.12 to 0.44, with substantially higher rates in richer provinces.

The MTR measures the marginal fiscal cost of overreporting. In 2013, overreporting 100 RMB of GDP implied about 12 RMB in additional central tax payments in Guizhou, but more than 40 RMB in Beijing and Shanghai. A more progressive redistribution rule therefore makes overreporting more costly, especially in rich provinces. This pattern is consistent with the regional heterogeneity in GDP misreporting shown in Figure 1.

3 A Model of GDP Misreporting and Regional Redistribution

In this section, I introduce a parsimonious model that links China's regional redistribution system to GDP overreporting under the political incentive system. The model builds on the Mandarin growth framework of Song and Xiong (2023), in which local officials report output to the central government to obtain political rewards. I extend this logic by allowing reported output to affect the fiscal payments that local governments make under the regional redistribution system. The main purpose of the model is to motivate the empirical design in the following sections. In particular, the model clarifies how promotion incentives and fiscal costs jointly determine GDP overreporting, and it generates the prediction that richer regions should overreport less when the redistribution system is progressive.

3.1 Environment

The economy consists of a set of regions indexed by i. Each region has a local government with a two-period term, a representative two-period-lived household, and a representative firm. The economy has a permanent central government.

I consider an economy that initially has neither redistribution nor political rewards. Before period t, the central government announces a tax schedule $T(\cdot)$, a political reward κ, and a value-added output tax rate τ_y. Given $(T(\cdot), \kappa, \tau_y)$, the local government collects taxes $\tau_y Y_i$ from the local firm and reports output $\psi_i Y_i$ to the central government. Tax revenues finance local government consumption G_i, public investment K_{Gi}, and central taxes based on reported output $T(\psi_i Y_i)$. Given local fiscal policy (K_G, G), households inelastically supply unit labor and choose household consumption, while firms produce. At the end of the period $t+1$, the local government receives political reward based on reported economic growth.

The progressive central tax function satisfies $T''(\cdot) > 0$, implying that the marginal tax rate increases with reported output. The log-linear tax function in Equation (1) with $\phi > 0$ is a special case.

Production is given by:

$$Y_{it} = A_{it} K_{Git}^{\theta} N_{it}$$

where A_{it} is exogenous TFP, K_{Git} is public capital, N_{it} is labor, and $0 < \theta < 1$ is the output elasticity of public capital. Capital depreciates fully after one period. The firm solves

$$\max_{N_{it}} (1 - \tau_y) Y_{it} - W_{it} N_{it}$$

which implies $W_{it} = (1 - \tau_y) Y_{it}$ with N_{it} normalized to 1.

A household born at period t solves

$$\begin{aligned} & \max \log C_{it}^{t} + \rho \log C_{it+1}^{t} \\ \text{s.t.} \quad & C_{it}^{t} + S_{it+1} \leq W_{it} \\ & C_{it+1}^{t} \leq (1 + R) S_{it+1} \end{aligned}$$

where ρ is the discounting rate and R is an exogenous interest rate. The resulting household utility depends only on current output:

$$U_i^t = (1 + \rho) \log Y_{it} + \Omega^U(\rho, \tau_y)$$

where Ω^U is constant.

Given predetermined (A_{it}, K_{Git}), the local government solves

$$\begin{aligned} \max_{K_{Git+1}, K_{Git+2}, \psi_{it+1}} \quad & U_i^{t+1} + \Theta \log K_{Git+2} + \chi(\log G_{it} + \rho \log G_{it+1}) + \kappa \log \left(\psi_{it+1} \frac{Y_{it+1}}{Y_{it}} \right) \\ \text{s.t.} \quad & G_{it} + K_{Git+1} \leq \tau_y Y_{it} \\ & G_{it+1} + K_{Git+2} \leq \tau_y Y_{it+1} - T(\psi_{it+1} Y_{it+1}) \end{aligned}$$

The local government values four objects: household utility during its term U_i^{t+1}, future household utility captured by $\Theta \log K_{Git+2}$, local government consumption $\chi(\log G_{it} + \rho \log G_{it+1})$, and political reward from reported output growth $\kappa \log \left(\psi_{it+1} \frac{Y_{it+1}}{Y_{it}} \right)$.

The model extends Song and Xiong (2023) to include the regional redistribution policy. For tractability, I make several assumptions without loss of generality. First, only the local governor values local government consumption and households do not. Also, only U_i^{t+1} enters the objective function since U_i^t solely depends on predetermined Y_{it}. Second, I include the reduced-form term $\Theta \log K_{Git+2}$ in the objective function only to avoid zero public capital. This term can be interpreted as the local governor's concern for future generations. Third, as I assume no political reward at period t, there is no incentive to overreport output. This is reasonable as current output reflects previous fiscal policies. Meanwhile, as I assume no redistribution policy in the first period, there is no incentive to underreport output. Under this setting, $\psi_{it} = 1$. Moreover, I assume that political reward is based on the observed economic growth, which aligns with the reality in China.[2] I assume no direct penalty for misreporting. The cost only arises from higher central taxes. Finally, I assume the production function satisfies diminishing returns to public capital and is linear in labor to guarantee that the output tax is not distortionary.

3.2 Model Implications for Overreporting

I focus on the qualitative implications for output overreporting. Details are provided in Appendix C. Output Y_{it+1} and output misreporting ψ_{it+1} are characterized by the first-order conditions (C1) and (C2). Equation (C1) characterizes the tradeoff in public investment: higher investment raises future government consumption, household utility, and political rewards, but lowers current government consumption. Equation (C2) characterizes the tradeoff in overreporting: overreporting raises political rewards but also raises taxes paid to the central government.

Proposition 1 decomposes observed convergence into actual convergence, driven by real output growth, and apparent convergence, driven by misreporting.

Proposition 1 (Decomposition of observed convergence)**.** *Observed economic conver-*

[2] The political reward can be micro-founded by the local governor's career incentive, as in Holmström (1999). Intuitively, the central government wants to promote high-ability local governors but cannot observe their ability. Therefore, the central government infers local governors' ability from reported performance. To appear high-ability, local governors invest in public capital and overreport economic performance. See Song and Xiong (2023) for details.

gence can be decomposed as

$$\frac{\partial \log(\psi_{it+1} Y_{it+1})}{\partial \log(Y_{it})} = \underbrace{\frac{\partial \log(Y_{it+1})}{\partial \log(Y_{it})}}_{\text{Actual Convergence}} + \underbrace{\frac{\partial \log(\psi_{it+1})}{\partial \log(Y_{it})}}_{\text{Misreporting}}$$

with

$$0 < \frac{\partial \log(Y_{it+1})}{\partial \log(Y_{it})} < 1$$

Assume that $T(y)$ is defined on $y > 0$ and satisfies $\lim_{y\to 0} T(y) = 0$ and $\lim_{y\to 0} T'(y)y = 0$. If $T''(y) \geq 0$, then high-output regions overreport less output growth:

$$\frac{\partial \log \psi_{it+1}}{\partial \log Y_{it}} \leq 0$$

with the equality if $T''(y) = 0$.

The assumption $\lim_{y\to 0} T(y) = 0$ ensures that zero-output regions pay no taxes, while $\lim_{y\to 0} T'(y)y = 0$ ensures the bounded limit of $T'(y)y$ near zero output. Proposition 1 shows that progressivity in the redistribution system is a sufficient condition for a negative relationship between overreporting and output. A higher marginal tax rate raises the marginal cost of overreporting more for high-output regions, while the marginal benefit of overreporting is common across regions. As a result, high-output regions overreport less than low-output regions.

If the tax scheme is linear or lump-sum, overreporting is independent of true output. In that case, $\psi_{it+1} = \tau_y \kappa / [T_c(\chi\rho + \kappa)]$ when $T'(\cdot) = T_c > 0$ is constant, or $\psi_{it+1} \to \infty$ when $T'(\cdot) = 0$. With a linear tax, the marginal cost of overreporting is uniform across regions, so every province overreports by the same amount.

Proposition 1 provides a simple theoretical foundation for the empirical analysis. The model shows that progressive redistribution raises the fiscal cost of overreporting more for high-output regions. Therefore, when the redistribution system becomes more progressive, GDP overstatement should become more negatively related to initial GDP. This prediction motivates the empirical analysis below, where I examine whether rich provinces reduced measured GDP overstatement relative to poor provinces after the 2002 tax reform.

Moreover, Corollary 1 links overreporting to political incentives that a higher political incentive κ increases the marginal return to inflating reported output and therefore induces more overreporting. This is not the core mechanism of the paper, but it provides a useful validation of the misreporting measure. When measuring GDP misreporting, we should observe higher overstatement in provinces where local officials have stronger promotion incentives.

Corollary 1. *The degree of output overreporting is increasing in political incentives:*

$$\frac{\partial \psi_{it+1}}{\partial \kappa} \geq 0.$$

4 Methodology

In this section, I describe how I detect misreporting of GDP growth in official statistics. Let y_i^* and y_i denote unobserved true GDP growth and official GDP growth, respectively. Suppose I observe two alternative measures, $x_{1,i}$ and $x_{2,i}$, which correspond to nighttime light growth and electricity consumption growth in the empirical application. The framework extends naturally to additional measures. Assumption 1 specifies the relationship among y_i, $x_{1,i}$, $x_{2,i}$ and y_i^*.

Assumption 1 (Data generating process)**.** *The relationship among y_i, $x_{1,i}$, $x_{2,i}$, and y_i^* is given by:*

$$y_i = y_i^* + \varepsilon_{y,i}$$

$$x_{1,i} = \alpha_1 y_i^* + \varepsilon_{1,i}$$

$$x_{2,i} = \alpha_2 y_i^* + \varepsilon_{2,i}$$

with $\mathrm{var}(y^*) = \sigma^2_{y^*}$, $\mathrm{var}(\varepsilon_y) = \sigma^2_{\varepsilon_y}$, $\mathrm{var}(\varepsilon_1) = \sigma^2_{\varepsilon_1}$, *and* $\mathrm{var}(\varepsilon_2) = \sigma^2_{\varepsilon_2}$.

I further impose the following assumption for identification.

Assumption 2 (Measurement error structure)**.** *The measurement error terms are mean independent of true GDP growth rates,*

$$\mathbb{E}[\varepsilon_y | y^*] = \mathbb{E}[\varepsilon_1 | y^*] = \mathbb{E}[\varepsilon_2 | y^*] = 0$$

and are uncorrelated with one another conditional on true GDP growth rates:

$$\mathbb{E}[\varepsilon_y \varepsilon_1 | y^*] = \mathbb{E}[\varepsilon_y \varepsilon_2 | y^*] = \mathbb{E}[\varepsilon_1 \varepsilon_2 | y^*] = 0$$

Assumptions 1 and 2 imply that official GDP growth is an unbiased estimator of true GDP growth and that the three measurement errors are uncorrelated conditional on true GDP growth. HSW impose the same structure in their framework with only two observables, y and x_1. With only official GDP and one proxy, the model is underidentified because there are three second-moment conditions, $\text{var}(y)$, $\text{var}(x_1)$, and $\text{cov}(y, x_1)$, for four unknown parameters $(\alpha_1, \sigma^2_{y^*}, \sigma^2_{\varepsilon_y}, \sigma^2_{\varepsilon_1})$. The novelty of my framework is to introduce an additional proxy whose measurement error is assumed to be uncorrelated with the measurement errors in both official GDP and nighttime lights. This is a strong assumption, but it may be plausible because electricity consumption data are typically reported by utility companies and are therefore less directly affected by governments' incentives to manipulate headline GDP figures.

I construct the best unbiased linear predictor of true GDP growth as

$$\hat{y}_i = \omega_y y_i + \omega_1 x_{1,i} + \omega_2 x_{2,i}$$

The weights $(\omega_y, \omega_1, \omega_2)$ are chosen to minimize the variance of the prediction error:

$$(\omega_y^*, \omega_1^*, \omega_2^*) = \arg \min_{\omega_y, \omega_1, \omega_2} \text{var}(y^* - \hat{y}) \tag{4}$$

subject to the constraint that the predictor is unbiased. That is, $\mathbb{E}[y^* - \hat{y} | y^*] = 0$, which implies:

$$\omega_y + \omega_1 \alpha_1 + \omega_2 \alpha_2 = 1$$

Define the signal-to-noise ratios of the three measures as

$$\gamma_y = \frac{\sigma^2_{y^*}}{\sigma^2_{\varepsilon_y}}, \quad \gamma_1 = \frac{\alpha_1^2 \sigma^2_{y^*}}{\sigma^2_{\varepsilon_1}}, \quad \gamma_2 = \frac{\alpha_2^2 \sigma^2_{y^*}}{\sigma^2_{\varepsilon_2}}$$

Solving the optimization problem (4) yields the optimal weights:

$$\omega_y^* = \frac{\gamma_y}{\gamma_y + \gamma_1 + \gamma_2}, \quad \alpha_1\omega_1^* = \frac{\gamma_1}{\gamma_y + \gamma_1 + \gamma_2}, \quad \alpha_2\omega_2^* = \frac{\gamma_2}{\gamma_y + \gamma_1 + \gamma_2}$$

Here, ω_y^* is the weight on official GDP growth, while $\alpha_1\omega_1^*$ and $\alpha_2\omega_2^*$ can be interpreted as the weights on growth predicted by nighttime lights, x_1/α_1, and electricity consumption, x_2/α_2, respectively. A measure with a higher signal-to-noise ratio receives a larger weight.

The variance of the prediction error is

$$\text{var}(y^* - \hat{y}) = \frac{1}{\frac{1}{\sigma_{\varepsilon_y}^2} + \frac{\alpha_1^2}{\sigma_{\varepsilon_1}^2} + \frac{\alpha_2^2}{\sigma_{\varepsilon_2}^2}} \leq \sigma_{\varepsilon_y}^2$$

so the optimal combination is always more precise than official GDP growth alone as long as the proxy is correlated with true GDP growth.

The model delivers six moments to identify six parameters. Proposition 2 states the result.

Proposition 2 (Identification)**.** *Under Assumptions 1 and 2, parameters* $\{\alpha_1, \alpha_2, \sigma_{y^*}^2, \sigma_{\varepsilon_y}^2, \sigma_{\varepsilon_1}^2, \sigma_{\varepsilon_2}^2\}$ *can be identified from the following moments:*

$$\text{var}(y) = \sigma_{y^*}^2 + \sigma_{\varepsilon_y}^2, \quad \text{var}(x_1) = \alpha_1^2\sigma_{y^*}^2 + \sigma_{\varepsilon_1}^2, \quad \text{var}(x_2) = \alpha_2^2\sigma_{y^*}^2 + \sigma_{\varepsilon_2}^2,$$
$$\text{cov}(y, x_1) = \alpha_1\sigma_{y^*}^2, \quad \text{cov}(y, x_2) = \alpha_2\sigma_{y^*}^2, \quad \text{cov}(x_1, x_2) = \alpha_1\alpha_2\sigma_{y^*}^2$$

In particular, the elasticity of nighttime light growth with respect to true GDP growth can be identified by the instrumental variable estimation:

$$\text{plim}\widehat{\alpha_1} = \text{plim}\frac{\text{cov}(x_1, x_2)}{\text{cov}(y, x_2)} = \frac{\alpha_1\alpha_2\sigma_{y^*}^2}{\alpha_2\sigma_{y^*}^2} = \alpha_1$$

The newly introduced electricity consumption measure therefore serves as an instrument for true GDP growth.

4.1 Potential Sources of Bias

Signal-to-noise ratio of official data. The variance of true GDP growth is estimated by

$$\widehat{\sigma^2_{y^*}} = \frac{\text{cov}(y, x_1)\text{cov}(y, x_2)}{\text{cov}(x_1, x_2)} = \frac{[\alpha_1 \text{var}(y^*) + \text{cov}(\varepsilon_y, \varepsilon_1)][\alpha_2 \text{var}(y^*) + \text{cov}(\varepsilon_y, \varepsilon_2)]}{\alpha_1\alpha_2 \text{var}(y^*) + \text{cov}(\varepsilon_1, \varepsilon_2)}$$

A positive correlation between official measurement error, ε_y, and measurement error in the two proxy variables, ε_1 and ε_2, tends to raise $\widehat{\sigma^2_{y^*}}$, thereby overstating the signal-to-noise ratio of official data. Intuitively, the estimator attributes comovement driven by correlated errors to the latent true-growth component, making official GDP appear more informative than it actually is. By contrast, a positive correlation between the measurement errors in nighttime lights and electricity consumption tends to lower $\widehat{\sigma^2_{y^*}}$, because this correlation is attributed to the signal in the proxies.

Civelli, Gaduh and Yousuf (2024) use nighttime lights and urban land cover as measures of economic activity. Since both variables are derived from satellite imagery, their measurement errors may share common remote-sensing components. In that case, positive correlation between the proxy-specific errors would lead the estimator to understate the signal-to-noise ratio of official GDP. In my setting, the three measures come from more distinct data-generating processes: official GDP is compiled by statistical agencies, nighttime lights are recorded by satellites, and electricity consumption is reported through the power company. This makes it less likely that the three measures share the same measurement errors.

Elasticities. The elasticity of measurement x_j ($j = 1, 2$) with respect to true GDP growth y^* can be estimated by:

$$\widehat{\alpha_j} = \frac{\text{cov}(x_1, x_2)}{\text{cov}(y, x_{-j})} = \frac{\alpha_1\alpha_2 \text{var}(y^*) + \text{cov}(\varepsilon_1, \varepsilon_2)}{\alpha_{-j} \text{var}(y^*) + \text{cov}(\varepsilon_y, \varepsilon_{-j})}$$

The bias works differently. A positive correlation between the measurement errors in the two proxy variables raises $\widehat{\alpha_j}$, making the proxy appear more responsive to true GDP growth and increasing its estimated optimal weight. By contrast, a positive correlation between measurement error in official GDP and that in the proxy used as the instrument lowers $\widehat{\alpha_j}$. In that case, the estimated optimal weight shifts toward official data.

5 Empirical Results: GDP Overreporting and Regional Convergence in China

5.1 Data

China's official data. Unless otherwise noted, all official Chinese data are sourced from the official website of the National Bureau of Statistics (NBS).[3] The NBS provides annual nominal regional GDP per capita and the growth rate of real regional GDP per capita. I construct real regional GDP per capita with the price deflated to the 1992 RMB level. I exclude Tibet from the analysis because of data reliability concerns and its unique treatment under various ethnic policies. Fiscal data are drawn from the Finance Yearbook of China (FYC) and the China Taxation Yearbook (CTY).

The NBS compiles the national account based on data collected by the local government. As Chen et al. (2019) points out, however, the NBS would use micro-level surveys, censuses, and administrative data to produce its own measurement for national GDP. This causes the discrepancy between national GDP and the sum of provincial GDP. Moreover, following economic censuses, the NBS will retroactively revise GDP series. This leads to the discrepancy between the historical data published in the China Statistical Yearbook (CSY) and the updated series available online. My analysis uses the revised data from the NBS website. I argue that even after these adjustments, significant GDP mismeasurement remains.

Global data. Global data are sourced from the World Bank dataset. Official GDP per capita data, population, and electric power consumption per capita come from the World Development Indicators (WDI). GDP is measured in constant local currency units, consistent with the approach for Chinese provinces. For countries with missing electric power consumption data in WDI, I supplement the data using the U.S. Energy Information Administration (EIA). The World Bank grades the statistical capacity of each country from 0 to 10. Following HSW, I classify countries with scores of 3 or lower as bad-data-quality. In addition, the World Bank classifies countries into low-, middle-, and high-income groups based on their gross national income (GNI) per capita and

[3]The NBS official website: https://data.stats.gov.cn/easyquery.htm?cn=E0103. It has an English version: https://data.stats.gov.cn/english/easyquery.htm?cn=E0103.

annual thresholds.

Nighttime light data. Nighttime light data are obtained from the National Oceanic and Atmospheric Administration's (NOAA) National Geophysical Data Center (NGDC). The NOAA provides satellite-year datasets from 1992 to 2013.[4] Each dataset reports the intensity of nighttime light for every 30 arc-second output pixel. The digital number of the nighttime light intensity is an integer between 0 (no light) and 63 (top-coded). See HSW and Pinkovskiy and Sala-i Martin (2016) for detailed introduction. To account for the variation in pixel size across latitudes, I compute the area-weighted average intensity of nighttime light for each administrative region.

As the intensity of nighttime light is associated with various factors, including living habits, economic structures, and population densities, it should not be interpreted as a direct proxy for GDP levels. For example, Canada's low average light intensity reflects its vast unpopulated regions instead of underdevelopment. Therefore, I associate nighttime light growth with economic growth and regard the growth in light intensity as a result of economic expansion.[5]

As noted in previous research, the original data provided by NOAA may suffer from top-coding (e.g., see Gibson et al. (2021)). According to HSW, only 0.1% of pixels are top-coded at DN 63, most of which are located in rich countries. Therefore, previous studies usually restrict their analysis to low- and middle-income countries. To address top-coding directly, Bluhm and Krause (2022) characterize the upper tail of nighttime lights using the Pareto distribution and recover the full distribution of city lights. To maintain comparability with previous research, I use the original NOAA data in the main text. In Appendix B, I replicate all results using the top-coding-corrected dataset. The main conclusions remain robust across the two datasets.

[4]Satellites include F10 (1992–1994), F12 (1994–1999), F14 (1997–2003), F15 (2000–2008), F16 (2004–2009), and F18 (2010-2013). Data are not comparable across satellites. Even within the same satellite, data may be biased due to sensor degradation. Therefore, I rely on long-term log differences to measure nighttime light growth. Growth from 1992/1993 to 2002/2003 uses satellites F10 and F14 and growth from 2002/2003 to 2012/2013 uses satellites F15 and F18.

[5]From an econometric perspective, using long-term log differences to measure nighttime light growth can eliminate time-invariant region-specific fixed effects.

5.2 Electricity Consumption as a Measure of Economic Activity

In the estimation, y is measured as the growth rate of official GDP per capita, x_1 as the growth rate of nighttime light intensity, and x_2 as the growth rate of electricity consumption per capita. Growth rates are measured as ten-year log differences to mitigate the influence of measurement error. Throughout the paper, GDP refers to GDP per capita.

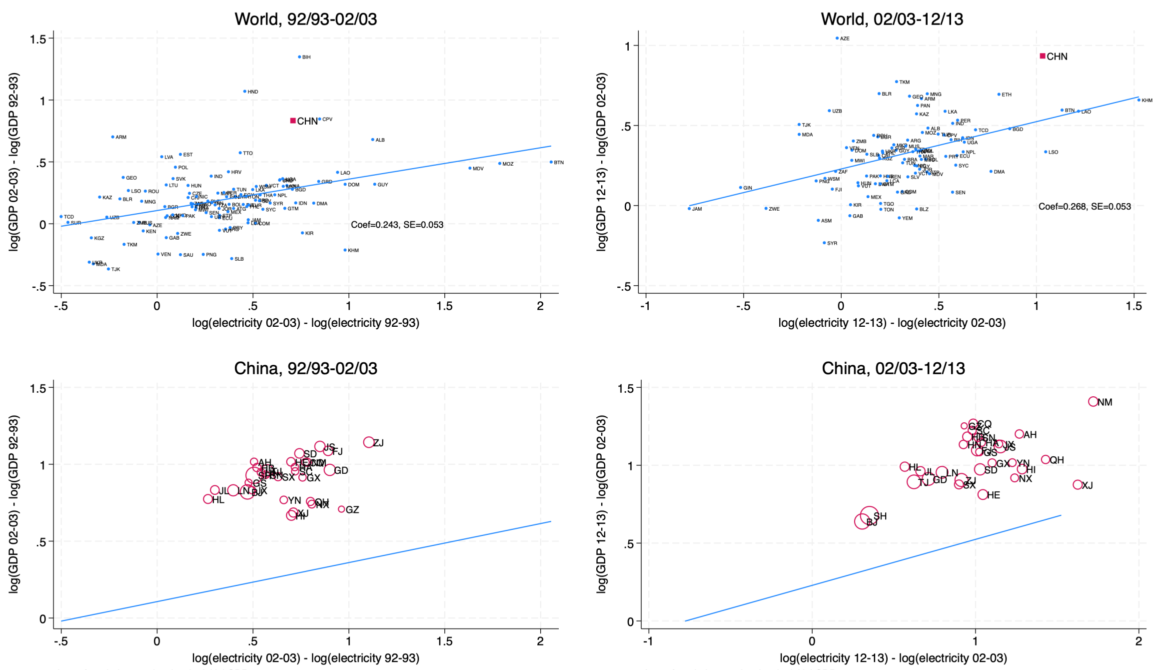
Electricity consumption is a natural third signal of economic activity. Electricity use is closely linked to production and is plausibly less directly affected by local officials' incentives to manipulate headline GDP. For this reason, electricity consumption has been used as an alternative indicator of Chinese economic activity, most notably in the Li Keqiang index, which combines electricity consumption with rail freight and bank lending. Related studies of Chinese data manipulation, including Wallace (2016) and Clark, Pinkovskiy and Sala-i Martin (2020), also use electricity consumption to evaluate the reliability of official GDP statistics. Moreover, electricity consumption is not derived from satellite imagery and is therefore less likely to share the same remote-sensing measurement errors as nighttime lights.

I begin the empirical analysis by documenting the relationship between electricity consumption growth and official GDP growth. This exercise serves two purposes. First, it provides evidence that electricity consumption contains useful information about economic activity. Second, it helps assess whether electricity consumption captures patterns similar to those documented using nighttime lights. Figure 2 replicates Figure 1 by plotting electricity consumption growth against official GDP growth in both the global sample and the Chinese provincial sample.

The top panel shows a strong positive relationship between electricity consumption growth and official GDP growth in the global sample. A 1% increase in electricity consumption growth is associated with a 0.24%–0.27% increase in GDP per capita, and the estimated relationship is stable across the two sample periods. This pattern supports the use of electricity consumption as an additional proxy for economic activity.

The bottom panel reports the same relationship for Chinese provinces. Before 2002, electricity consumption growth is not significantly correlated to official GDP growth across provinces. After 2002, however, the relationship becomes positive and more pronounced. This pattern is similar to the one observed using nighttime lights: in the post-2002 period, poorer provinces tend to report higher GDP growth relative to the growth implied by physical indicators of economic activity, while richer provinces lie closer to the fitted relationship. The similarity between the nighttime-light evidence and the electricity evidence suggests that the main pattern is not driven solely by satellite-specific measurement error, such as sensor saturation or top-coding. Instead, both physical proxies point to a change in the cross-provincial pattern of official GDP growth after 2002.

Figure 2: GDP Growth and Electric Power Consumption Growth, World and Chinese Provinces



Note: These figures plot the growth in GDP against the growth in electric power consumption from 1992/1993 to 2002/2003 (left) and from 2002/2003 to 2012/2013 (right). The y-axis represents changes in log GDP while the x-axis represents changes in log of electricity consumption. The world sample includes low- and middle-income countries which have good-quality official GDP data. The solid line is the fitted line estimated from the global data. Each dot in the top panel represents a country; in the bottom panel, a Chinese province. In the bottom panel, the dot size is proportional to initial GDP per capita.

To further assess the relationship between the two proxy measures of economic activity, Table 1 regresses official GDP growth on nighttime light growth and electricity consumption growth. Both measures are strong predictors of official GDP growth. Although nighttime lights and electricity consumption are correlated, electricity consumption growth remains positively and significantly correlated with official GDP growth after controlling for nighttime light growth. This suggests that electricity data provide additional predictive variation that can be used to measure economic activity. This variation may reflect industrial production, indoor commercial activity, household appliance use, and energy-intensive production that nighttime lights do not fully capture. For example, in Section 6.2, I show that nighttime lights are more sensitive to service-sector growth, whereas electricity consumption is more sensitive to industrial growth. Therefore, including electricity consumption as a third signal can improve the measurement of economic activity.

Table 1: Regression of Official GDP Growth on Growth of Nighttime Light and Electricity Consumption

	Official GDP Growth					
	1992/93-2002/03			2002/03-2012/13		
	(1)	(2)	(3)	(4)	(5)	(6)
Nighttime Light Growth	0.292		0.211	0.329		0.235
	(0.098)		(0.117)	(0.062)		(0.073)
Electricity Consumption Growth		0.254	0.150		0.284	0.156
		(0.054)	(0.054)		(0.058)	(0.068)
Constant	0.061	0.107	0.046	0.173	0.236	0.167
	(0.043)	(0.028)	(0.043)	(0.039)	(0.032)	(0.039)
R^2	0.199	0.165	0.241	0.224	0.185	0.261

Note: Robust standard errors are reported in parentheses. The sample includes low- and middle-income countries whose statistical capacity score exceeds 3.5 out of 10. The sample size is 107 for 1992/93–2002/03 and 92 for 2002/03–2012/13.

5.3 Parameterization

I estimate the structural parameters according to Proposition 2 and report the results in Table 2. Panel A reports the parameter estimates, and Panel B reports the implied optimal weights. The sample selection criterion closely follows HSW. Because the elasticity of nighttime lights with respect to GDP may vary with income, I exclude high-income countries. I also exclude countries whose statistical capacity score is below 3.5 out of 10. Robust standard errors computed using the delta method are reported in parentheses.

First, the elasticity of nighttime light growth with respect to true GDP growth is about 1.9, implying that the long-run growth rate of nighttime lights is roughly twice the long-run growth rate of true GDP. This estimate is above the benchmark estimate of 1.1 in HSW under the assumption $\phi_y = 9$, and also above the estimate of 1.3 in Hu and Yao (2022). The difference partly reflects the fact that my framework assigns a lower weight to official GDP growth than previous approaches. Meanwhile, the elasticity of electricity consumption with respect to true GDP growth is about 1.8. Both elasticities are statistically significant and stable across sample periods.

Second, the implied weights on official GDP, nighttime lights, and electricity consumption are about 20%, 50%, and 30%, respectively. Thus, the optimal measure relies more heavily on the two physical indicators than on official GDP data. This suggests that nighttime lights and electricity consumption contain substantial information about economic activity beyond official statistics. My weight on nighttime light growth is higher than, but comparable to, the results in Hu and Yao (2022). In their framework, which combines only official GDP and nighttime lights, the mean country-specific weight on light-predicted growth is 65%.

The relatively low estimated weight on official GDP raises a natural concern about potential bias. The most vulnerable assumption in my framework is that the measurement error in electricity data is uncorrelated with that in official GDP. In practice, because both series are collected and reported by people, and because autocratic governments may adjust GDP and electricity growth in the same direction, measurement errors in official GDP and electricity data may be positively correlated. In that case, as discussed in Section 4.1, the estimated variance of true GDP growth is upward biased when $\text{cov}(\varepsilon_y, \varepsilon_2) > 0$. Therefore, the weight on official data is unlikely to be underestimated.

Panel C reports the difference between the official GDP growth and the optimal measure I constructed for selected countries. Positive values indicate that official data may overstate GDP growth. My estimates are broadly comparable to those in Hu and Yao (2022). During 1992/93–2002/03, the annual differences are 4.2, 1.8, 0.1, and 0.6 for China, India, Brazil, and South Africa, respectively, while the corresponding values in their calibration for 1992-2001 are 3.7, 1.8, -0.4, and -0.5. During the period from 2002/03–2012/13, my estimates for these countries are 3.2, 1.1, -0.7, and 0.1, while their corresponding values for 2001-2007 (2008-2013) are 3.9 (3.1), 1.6 (1.5), -0.7 (0.0), and -0.3 (-0.8). Although the two papers use different methodologies and produce somewhat different elasticity estimates, the implied patterns of GDP growth mismeasurement are broadly similar, which lends support to my framework and estimation.

Table 2: Estimation Results

	1992/93–2002/03	2002/03–2012/13
Panel A. Estimated parameters		
α_1	1.939	1.916
	(0.435)	(0.476)
α_2	1.852	1.834
	(0.725)	(0.454)
$\sigma^2_{y^*}$	0.025	0.018
	(0.014)	(0.007)
$\sigma^2_{\varepsilon_y}$	0.046	0.033
	(0.011)	(0.009)
$\sigma^2_{\varepsilon_1}$	0.072	0.039
	(0.024)	(0.013)
$\sigma^2_{\varepsilon_2}$	0.096	0.056
	(0.031)	(0.014)
Panel B. Implied optimal weights		
ω_y	0.198	0.165
$\omega_1\alpha_1$	0.477	0.511
$\omega_2\alpha_2$	0.325	0.324
Panel C. GDP Misreporting of Selected Countries (percentage point, annually)		
China	4.2	3.2
India	1.8	1.1
Brazil	0.1	-0.7
South Africa	0.6	0.1

Note: Robust standard errors are reported in parentheses. The sample includes low- and middle-income countries whose statistical capacity score exceeds 3.5 out of 10. The sample size is 107 for 1992/93–2002/03 and 92 for 2002/03–2012/13. Panel C reports the annual percentage-point difference between official GDP growth and the optimal measure.

5.4 GDP Misreporting and Regional Convergence

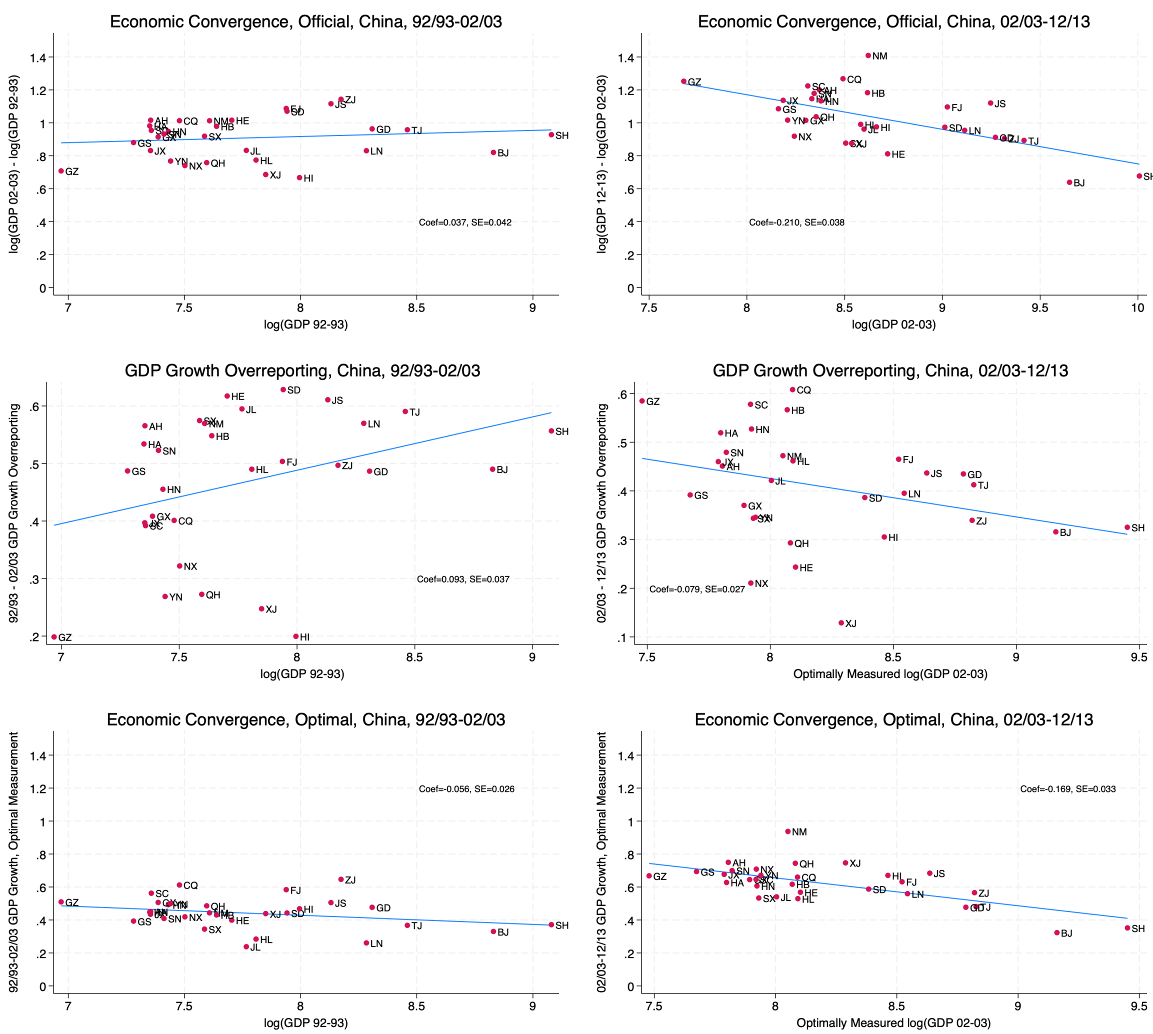
Motivated by Proposition 1, I decompose observed convergence in official statistics into true convergence and a misreporting component. I begin by estimating economic convergence using China's official GDP data. The regional convergence rate is estimated using the Barro-style regression (Barro and Sala-i Martin, 1992). The top panel of Figure 3 plots long-run official GDP growth against initial GDP. Prior to 2003, provinces experienced an average annual growth rate of 9.1%, with no significant correlation between growth and initial GDP. From 2002/2003 to 2012/2013, poorer provinces grew faster than richer ones. The estimated annual convergence rate is 2.1% and is significantly different from zero. This implies that it takes about 30 years to cut the GDP gap between any two provinces by half.

Next, I use the difference between official GDP growth and the optimal measure to capture GDP overreporting. The middle panel of Figure 3 plots GDP overreporting against initial GDP. From 1992/93 to 2002/03, provinces overreport GDP growth by 4.5 percentage points per year on average, which is above the national figure of 4.2 reported in Table 2. Similarly, from 2002/03 to 2012/13, provinces overreport GDP growth by 4.1 percentage points per year on average, while the corresponding national figure is 3.2. This reflects the fact that the central government takes local overreporting into account when constructing the national accounts.

To improve promotion prospects, local officials have incentives to exaggerate economic performance. However, the cross-province pattern of overreporting changes over time. Before 2002, richer provinces exhibit higher measured GDP overstatement than poorer provinces. After the 2002 tax reform, however, measured overstatement among poor provinces remains roughly unchanged, while richer provinces reduce overstatement substantially. A 10 percent higher initial GDP level is associated with a 0.8 percentage-point decline in annual overreported GDP growth. This pattern is consistent with Proposition 1: when redistribution becomes more progressive, richer regions face a higher marginal fiscal cost of overreporting and therefore reduce overstatement relative to poorer regions.

After correcting for overreported GDP growth, the bottom panel of Figure 3 plots the optimally measured growth rates against initial GDP. While official data imply neither economic convergence nor divergence from 1992 to 2002, the optimal measure implies slow regional convergence at an annual rate of 0.5%. After 2002, regional convergence remains substantial, but the estimated convergence rate declines from 2.1% in official data to 1.7% in the optimal measure. The implied half-life of GDP gaps rises to 40 years. Hence, GDP overreporting can account for roughly 20% of the convergence observed in official data.

Figure 3: Regional Convergence from Official Data and the Optimal Measure, and GDP Misreporting in Chinese Provinces, 1992–2013



Note: In the right-middle and right-bottom panels, the x-axis is the log of optimally measured GDP in 2002/03, calculated as GDP in 1992/93 multiplied by the constructed growth rates.

6 Discussion

What accounts for the rapid convergence in China's official GDP data? I argue that the regional redistribution system is an important part of the answer. After the 2002 tax reform, the central government collected a larger share of fiscal revenue from local governments and expanded transfers to less developed regions. Under this system, overreporting GDP growth becomes more costly for rich provinces: higher reported output is associated with higher payments to the central government and fewer transfers received. As shown in Figures A1 and A2, the estimated progressivity of the regional redistribution system increased over time, and rich provinces experienced larger increases in marginal tax rates. This raised the marginal cost of overreporting especially for high-income local governments. Consistent with this interpretation, Figure 3 shows that poor regions continued to exaggerate economic performance, whereas rich regions reduced overstatement substantially.

At the same time, the increasingly progressive redistribution system directed more resources toward low-productivity regions. As poor regions received more resources to invest, they experienced faster economic growth. By contrast, higher marginal tax rates reduced the incentives of rich local governments to implement pro-growth policies such as infrastructure investment. As a result, rich regions grew more slowly than poor regions. This helps explain why substantial regional convergence remains after correcting for GDP misreporting in Figure 3.

Because the 2002 tax reform was implemented nationwide, it does not provide a natural untreated control group, and the full mechanism is difficult to identify directly in a reduced-form framework. As an additional descriptive exercise, I regress the change in overreported growth on the change in the implied marginal tax rate between the two periods. The coefficient (standard error) is -1.67 (0.45), indicating that provinces experiencing a larger increase in the fiscal cost of overreporting exhibit a larger decline in GDP overstatement. Since changes in implied MTR are themselves mechanically related to provincial income, I interpret this result as descriptive rather than causal. I next address several alternative explanations that could affect the interpretation of the overstatement patterns.

6.1 Misreporting or Mismeasurement?

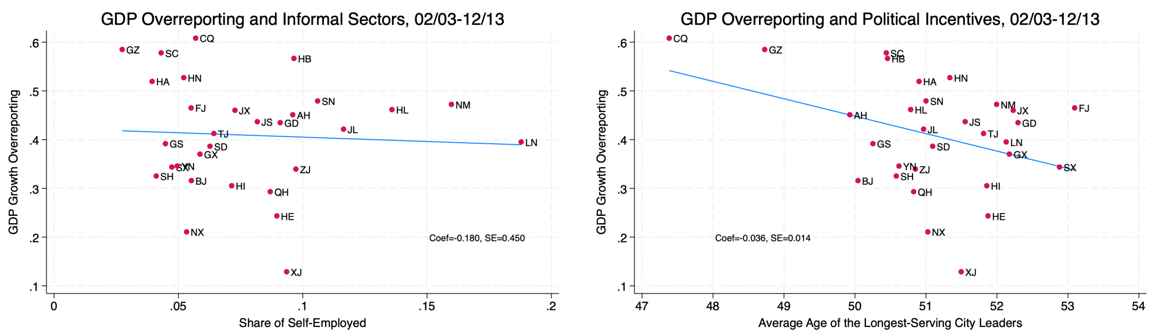
Even if my constructed optimal measure is indeed closer to true GDP growth, the difference between that measure and official data may reflect mismeasurement rather than strategic misreporting. This concern is plausible because poor regions often have larger informal sectors, which are harder for official statistics to capture, especially when local statistical capacity is weak (Jerven, 2013; Medina and Schneider, 2018). Under this interpretation, the pattern in Figure 3 could arise because informal activity shrinks with development, allowing a larger share of economic activity to be captured in official statistics.

I address this concern in two ways. First, I use the share of self-employed workers in total employment as a proxy for the size of the informal sector. I find that overreported GDP growth is uncorrelated with this measure, as shown in the left panel of Figure 4. Second, if improved measurement of informal activity were the main explanation, one would expect the gap between poor and rich regions to narrow because poor regions become better measured over time. By contrast, Figure 3 shows that the main change comes from rich regions reducing overstatement. This pattern is therefore difficult to reconcile with a pure mismeasurement explanation.

According to Corollary 1, overstatement of output growth should be higher in provinces where officials have higher political incentives. To provide external validation of my measure of GDP misreporting, I follow Yao and Zhang (2015), Song and Xiong (2023), and Zeng and Zhou (2024) and use the age of local leaders as a proxy for political incentives. Younger local officials face stronger promotion incentives and are therefore more likely to overreport GDP growth. The right panel of Figure 4 shows that provinces with younger local officials tend to have higher measured GDP overstatement.

Moreover, in Figure A3, I show that the age of local officials is not correlated with initial GDP. This suggests that the central government does not systematically assign younger or more experienced officials to regions with particular income levels. Therefore, the negative relationship between measured GDP overstatement and initial GDP is unlikely to be driven by the cross-regional assignment of local officials, at least with respect to age. Thus, the political-incentive pattern supports the interpretation that the measured gap between official GDP growth and proxy-based growth reflects strategic overreporting rather than mismeasurement.

Figure 4: Informal Sectors, Political Incentives, and Measured GDP Overstatement



Note: In the left panel, the x-axis is the share of self-employed workers in total employment. In the right panel, the x-axis is the average age of the longest-serving city leaders, including party secretaries and mayors, within a province. In Figure A3, I replace the explanatory variable with the average age of all city leaders and the average age of the two longest-serving city leaders. The results remain robust. Data on local officials are compiled by Jiang (2018).

6.2 Structural Change

Beyer et al. (2018) raise a concern that nighttime lights may be more strongly associated with service-sector activity than with industrial activity. If so, the finding that rich regions exhibit lower GDP overreporting could simply reflect the fact that these regions have larger service sectors and therefore stronger nighttime light growth.

I address this concern in two ways. First, using the same global country sample, I regress nighttime light growth and electricity consumption growth on total value-added growth by sector. For nighttime lights, the estimated coefficients (standard errors) are 0.48 (0.09) for industry and 0.56 (0.16) for services. The difference is economically small, suggesting that nighttime lights do not capture service-sector growth disproportionately enough to drive the main results. For electricity consumption, the corresponding coefficients are 0.46 (0.13) for industry and 0.39 (0.23) for services. This pattern suggests that, while nighttime lights are somewhat more sensitive to services, electricity consumption is more sensitive to industry. Although these regressions may themselves be biased by measurement error and should not be given a structural interpretation, they are still informative about the relative sectoral sensitivities of the two proxies. Taken together, combining nighttime lights and electricity consumption helps mitigate sector-specific measurement bias.

Second, for China, I use sectoral employment shares to capture structural change. I do not use sectoral value-added shares because they are constructed from official GDP data and may therefore inherit the same reporting bias studied in this paper. Regressions of overreported GDP growth on the initial employment shares of the secondary and tertiary sectors yield insignificant coefficients. This suggests that structural change is unlikely to be the main explanation for the observed overreporting patterns. In the next subsection, I will further address this issue by estimating varying elasticities across income groups.

6.3 Varying Elasticities Across Income Groups

Similar to the concern about structural change, HSW emphasize that the elasticity of nighttime light growth with respect to GDP growth may vary by income level. They therefore restrict their sample to low- and middle-income countries. This concern is reasonable because urban growth may take different forms across income groups. In developing countries, urbanization often involves the spatial expansion of lit areas, which can lead to rapid increases in nighttime lights. In developed countries, by contrast, additional economic activity is more likely to be accommodated through vertical densification rather than outward expansion. Because satellite-based nighttime lights mainly capture surface luminosity, this form of growth may translate into weaker increases in measured light intensity.

To address this concern, Table 3 estimates the elasticities separately by income group. Since high-income countries are more likely to be affected by top-coding, I use the top-coding-corrected nighttime lights compiled by Bluhm and Krause (2022) in this exercise. The estimates suggest that high-income countries have lower elasticities of nighttime light growth with respect to true economic growth than low- and middle-income countries. The elasticity of electricity consumption shows a similar pattern. One possible explanation is that economic development is associated with structural transformation toward less energy-intensive sectors and with improvements in energy efficiency. As a result, a given increase in economic activity may translate into smaller increases in electricity consumption in richer economies. I further split middle-income countries into lower-middle- and upper-middle-income groups. The broader pattern remains similar that richer countries tend to have lower elasticities.

To see how this affects the estimation, I recalculate GDP misreporting for each province using heterogeneous elasticities. Beijing and Shanghai reached income levels comparable to high-income economies after 2010. I therefore recalculate their GDP misreporting using the elasticity estimated from the high-income-country sample, while using the middle-income elasticity for other provinces. Figure 5 plots the recalculated GDP overstatement against initial GDP. The negative relationship remains: provinces with higher initial GDP still exhibit lower measured overstatement of GDP growth. In Figure A4, I further classify Tianjin, Zhejiang, Jiangsu, and Guangdong as high-income regions and repeat the exercise. The relationship remains robust. These results suggest that the main pattern is unlikely to be driven by top-coding or by differences in proxy elasticities across income groups.

The negative relationship between GDP overstatement and initial income becomes more pronounced (compared to the mid-right panel of Figure B5) when I allow elasticities to vary across income groups. The intuition is straightforward. If high-income regions have lower elasticities of nighttime light growth and electricity consumption growth with respect to true economic growth, then the same observed growth in nighttime lights and electricity consumption implies higher true economic growth for these regions. This raises the constructed measure of true GDP growth and therefore lowers measured GDP overstatement. As a result, rich regions exhibit even less GDP overstatement under heterogeneous elasticities than under the baseline specification with common elasticities.

6.4 Extension: GDP Misreporting and Global Convergence

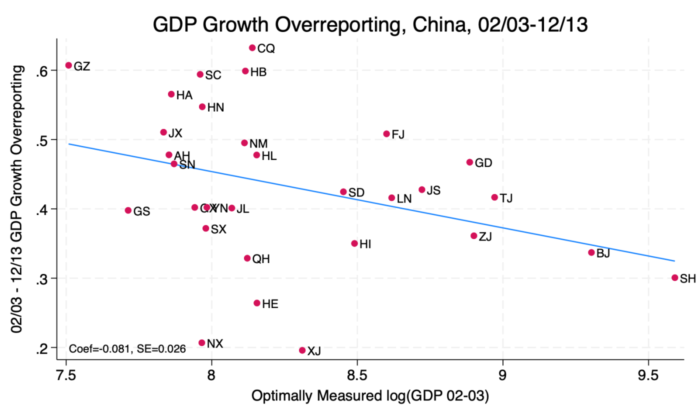
So far, I have shown that regional heterogeneity in GDP overreporting accounts for the appearance of rapid convergence in China. This raises a broader question: does GDP misreporting also affect measured convergence in global data? Existing studies typically rely on official GDP data and find limited evidence of convergence. As an additional application, in this part, I use nighttime light and electricity consumption to obtain better measurement of economic growth and uncover the convergence pattern in global

Table 3: Elasticities by Income Group, Data Corrected for Top-Coding

	Low (1)	Middle (2)	Lower-Middle (3)	Upper-Middle (4)	High (5)
α_1	1.886	1.952	2.345	1.385	1.147
	(0.792)	(0.585)	(0.679)	(0.637)	(0.403)
α_2	3.470	1.361	1.508	1.056	1.158
	(1.364)	(0.383)	(0.583)	(0.369)	(0.337)
Observations	15	77	35	42	49

Note: Robust standard errors are reported in parentheses. The low- and middle-income groups include only countries with good official data quality. The middle-income group pools lower-middle- and upper-middle-income countries; columns (3) and (4) report estimates separately for these two subgroups.

Figure 5: Recalculated GDP Misreporting Using Income-Group-Specific Elasticities



Note: Beijing and Shanghai are assigned the elasticities estimated from the high-income-country sample. All other provinces are assigned the elasticities estimated from the middle-income-country sample.

areas. Figure 6 compares the convergence patterns implied by official data and by the optimal measure for Africa, the Americas, Asia, and Europe. In each panel, squares and diamonds denote countries whose official GDP growth is potentially overestimated and underestimated, respectively. I do not adjust growth rates for high-income countries, which is denoted by circles.[6]

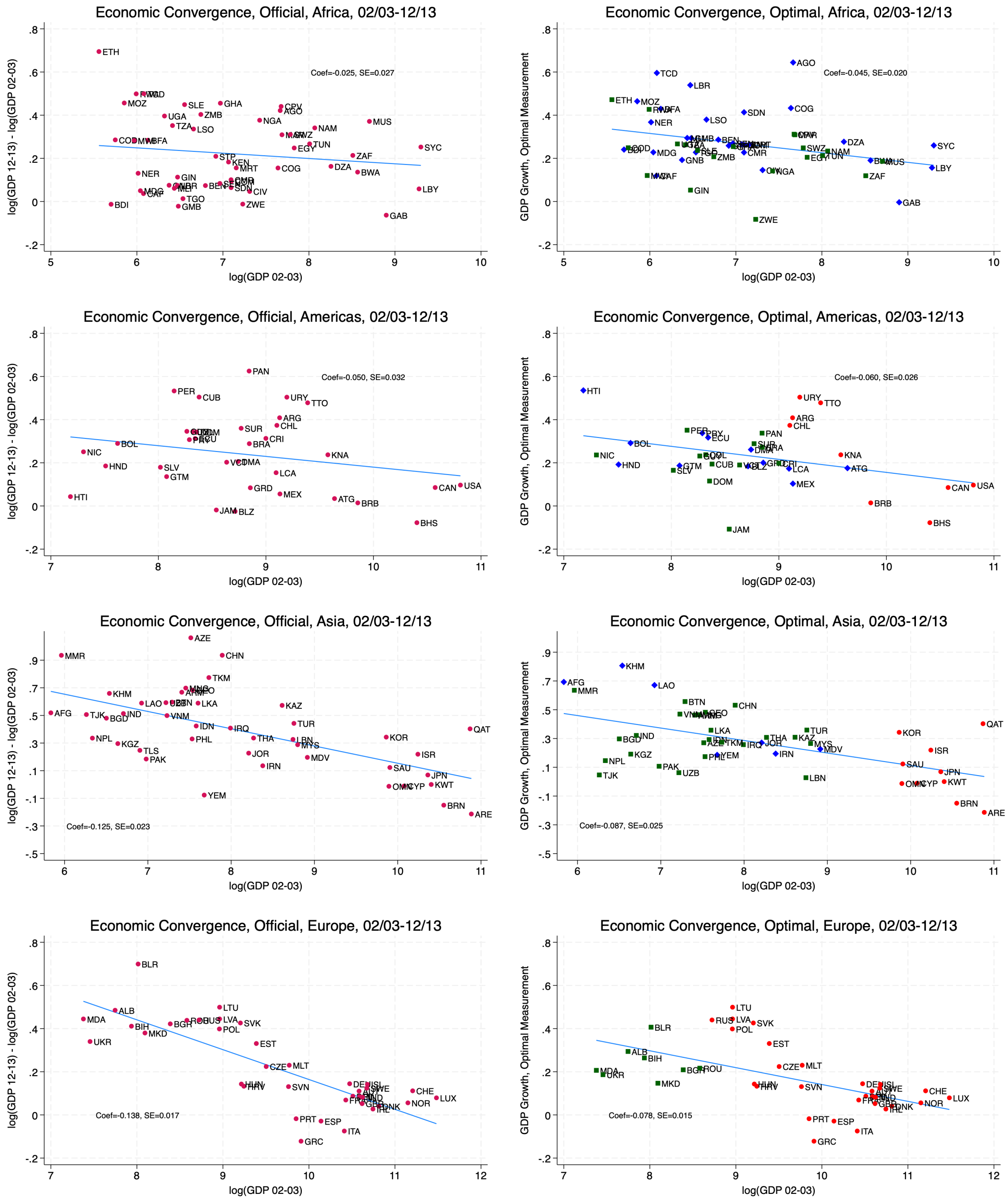
The top panel shows that official data tend to understate economic growth in Africa, especially among the poorest countries. Official data imply an average annual GDP growth rate of 2.2%, whereas the optimal measure implies 2.7%. While official data show no relationship between growth and initial GDP, the optimal measure implies unconditional convergence within Africa, with an annual convergence rate of 0.5%. The pattern is similar in the Americas. In the top-middle panel, growth among the poorest countries is also understated. Although official data show no convergence, the optimal measure implies an annual convergence rate of 0.6%. This understatement of growth in Africa and the Americas is consistent with weak statistical capacity and large shadow economies (Ghosh et al., 2009; Young, 2012; Jerven, 2013; Medina and Schneider, 2018).

Unlike Africa and the Americas, the bottom-middle panel of Figure 6 shows systematic overstatement of growth in Asia. Following Martinez (2022) and using the Freedom in the World index, I find that "Not free" countries such as Azerbaijan, Turkmenistan, Uzbekistan, Myanmar, and Tajikistan tend to overstate economic growth. While official data imply an annual convergence rate of 1.3%, the optimal measure implies a lower rate of 0.9%. A similar pattern appears in Europe. The bottom panel suggests overstatement of economic growth, particularly in "not free" countries such as Belarus and in "partially free" countries such as North Macedonia, Albania, Moldova, and Bosnia and Herzegovina. Official data imply an annual convergence rate of 1.4%, whereas the optimal measure implies 0.8%.

In sum, nighttime lights and electricity consumption reveal distinct patterns of GDP misreporting and convergence across regions. Growth appears to be systematically

[6]Following HSW, I group low- and middle-income countries by statistical capacity. I use countries with good data quality to estimate the parameters reported in Table 2, assume that the proxy elasticities and measurement-error distribution are common across countries, and then re-estimate the variance of official measurement error for countries with poor statistical capacity. I use these estimates to construct the corresponding optimal weights for countries with poor data quality.

Figure 6: Global Convergence: Official Data and the Optimal Measure



Note: In the right panels, circles denote unadjusted countries, squares denote countries with potentially overestimated growth, and diamonds denote countries with potentially underestimated growth. The sample includes countries with available World Bank GDP data. GDP is measured in constant U.S. dollars.

understated in Africa and the Americas, consistent with poor data quality and large shadow economies. By contrast, growth appears to be overstated in parts of Asia and Europe, especially in less free regimes. As a result, the optimal measure implies lower convergence in Asia and Europe and uncovers unconditional convergence in Africa and the Americas.

7 Conclusion

This paper uses nighttime lights and electricity consumption to construct a measure of potential GDP overstatement and to reassess observed patterns of economic convergence. Methodologically, it builds on the HSW framework by introducing electricity consumption as an additional proxy for economic activity. Whereas Hu and Yao (2022) use auxiliary information on statistical capacity and geography to infer measurement error, I use a third signal to recover the parameters of the measurement system under a parsimonious set of assumptions. This extension improves the precision of the constructed growth measure and provides a transparent way to compare official GDP growth with growth implied by physical indicators of economic activity.

Empirically, I apply this framework to Chinese provinces and show that part of the rapid regional convergence in official data reflects declining measured GDP overstatement by rich regions. I interpret this pattern through China's political and fiscal institutions. While existing work, such as Martinez (2022) and Song and Xiong (2023), emphasizes incentives to overstate growth, I highlight the fiscal cost of doing so. China's regional redistribution system raises the marginal cost of overreporting for richer regions, especially as redistribution becomes more progressive. As a result, rich provinces reduce overstatement relative to poor provinces, contributing to artificially rapid convergence in official statistics. The theoretical framework highlights how information frictions can interact with fiscal policy, making it useful for future welfare analysis and policy evaluation.

As an additional application, I extend the measurement exercise to global data. The adjusted growth measure suggests stronger convergence in Africa and the Americas, but weaker convergence in Asia and Europe. These results indicate that cross-country differences in statistical capacity, informality, and political incentives can distort measured growth and affect our understanding of convergence. Taken together, this paper shows that measurement error in official statistics is not only a data problem, but can shape substantive conclusions about long-run development.

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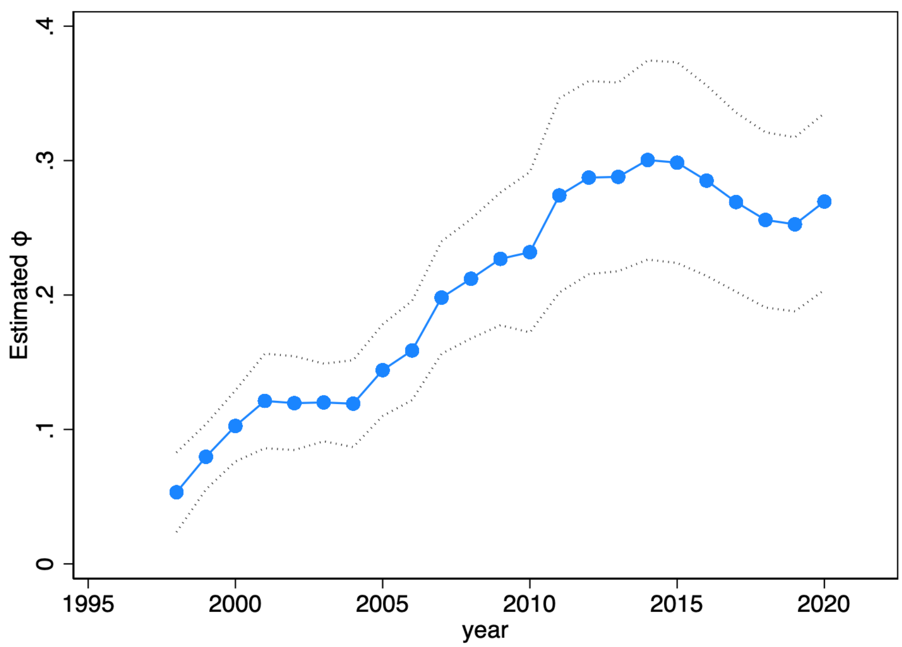
Supplemental Online Appendix

A Supplementary Figures

This section provides supplementary figures related to the main text. Figure A1 plots the estimated progressivity of the regional redistribution system from regression (3). The estimated progressivity increases over time, especially after the 2002 tax reform. Progressivity does not rise immediately after the reform. Although the reform increased the tax revenue collected from richer local governments, the central government also provided compensation transfers to these regions during the transition period. As a result, estimated progressivity remains relatively stable during the reform period before rising sharply afterward.

Figure A1: Estimated Progressivity of Redistribution System



Note: Each dot represents the estimated ϕ from Regression (3). Dotted lines are 95% confidence intervals.

Figure A2 plots the theoretical marginal tax rates (MTRs) implied by Equation(2). The MTR measures the additional payment to the central government associated with a marginal increase in local GDP per capita. In 1997, when progressivity was relatively low, differences in MTRs across regions were small. The poorest regions faced an MTR of around 5%, while the richest regions faced an MTR of around 15%. Fifteen years later, as progressivity increased to about 0.3 in 2013, the poorest regions faced an MTR of around 15%, while rich regions faced MTRs above 40%. This indicates that the marginal fiscal cost of overreporting GDP rose substantially for developed regions.

Figure A2: Theoretical Marginal Tax Rate

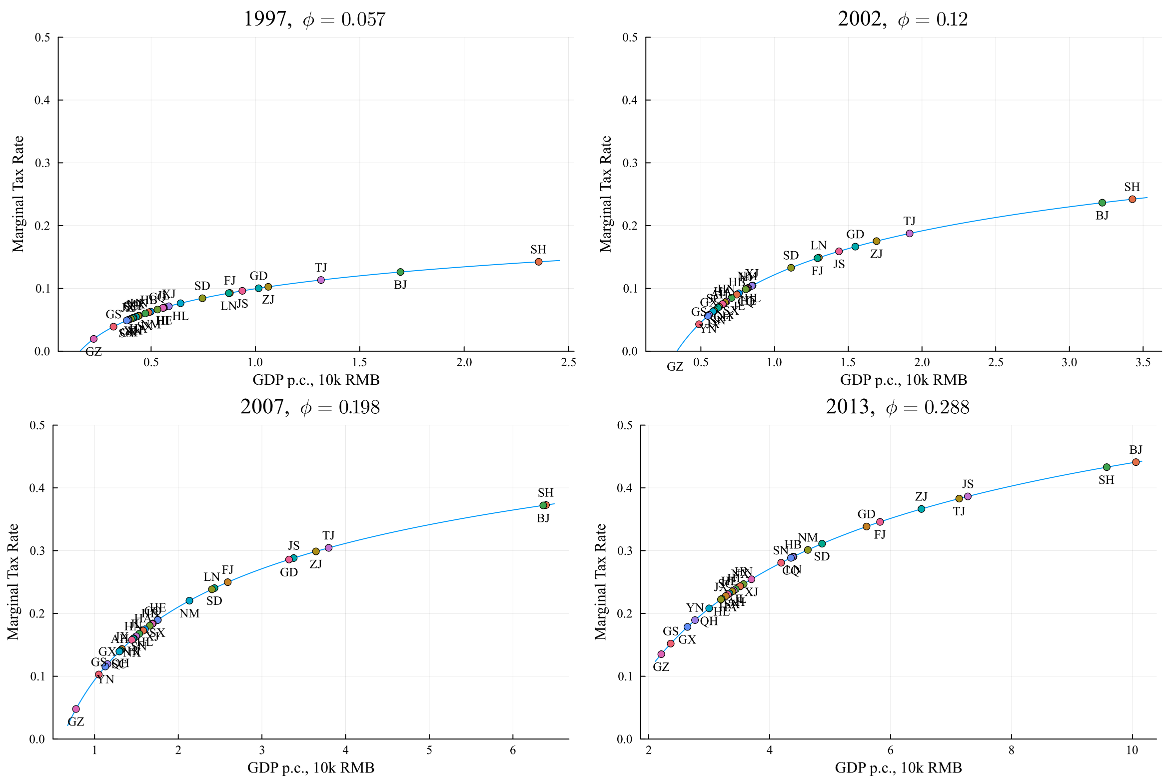
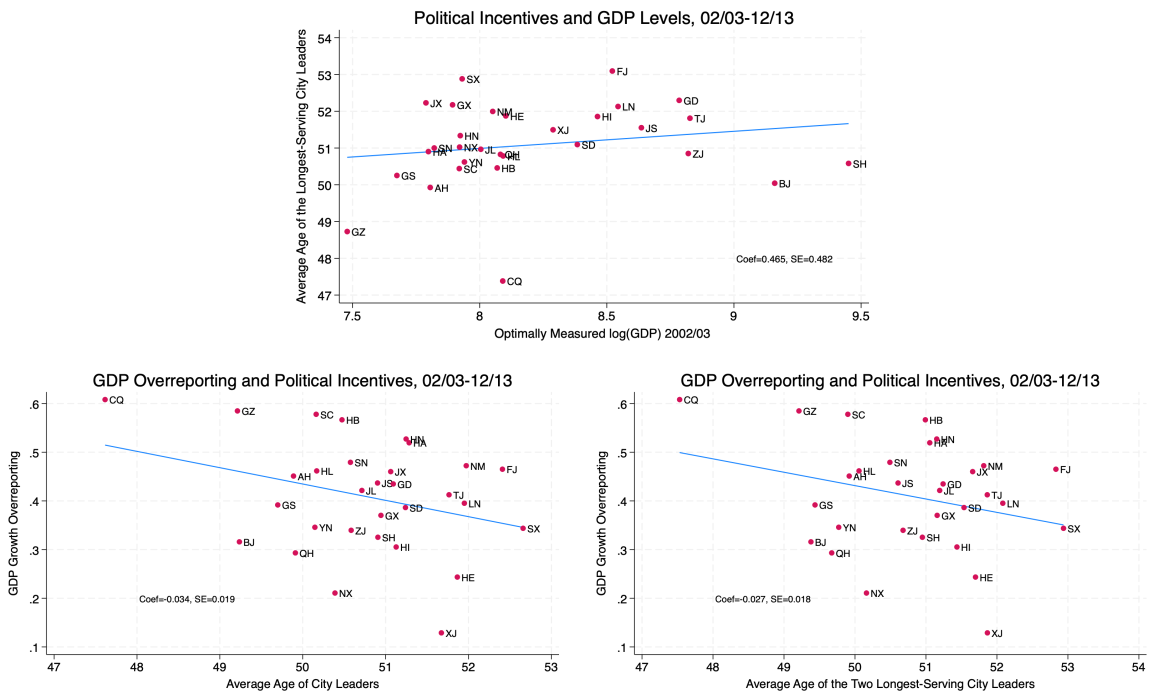


Figure A3 provides additional evidence on the relationship between political incentives and measured GDP overstatement. The top panel first shows that the age of local officials is not correlated with initial GDP levels. This suggests that the central government does not systematically assign younger or more experienced officials to regions with particular income levels, at least with respect to age. In the bottom panels, I replace the explanatory variable in Figure 4 with the average age of all city leaders and with the average age of the two longest-serving city leaders. Although the estimates are less precise, the negative relationship between measured GDP overstatement and the age of local officials remains. The decline in precision is likely due to short-term rotations of local officials in China. These officials may have less influence on local policy and official statistics, but they add noise to the measurement of political incentives.

Figure A4 replicates the exercise in Figure 5 while additionally classifying Tianjin,

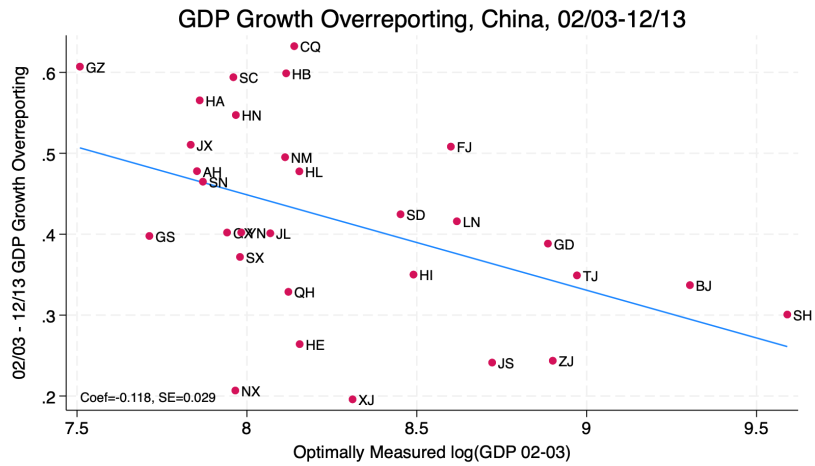
Figure A3: Political Incentives, and Measured GDP Overstatement, Alternative Measurements



Note: in the bottom panel, the x-axis represents the average age of all city leaders (left) and the average age of the two longest-serving city leaders (right).

Zhejiang, Jiangsu, and Guangdong as high-income regions. As discussed in the main text, this makes the negative relationship between measured GDP overstatement and initial GDP more pronounced.

Figure A4: Recalculate GDP Misreporting using Varying Elasticities



Note: Beijing, Shanghai, Tianjin, Zhejiang, Jiangsu, and Guangdong are categorized as high-income regions.

B Main Results Using Top-Coding-Corrected Data

This section replicates the main exercises in Sections 5 and 6 using the top-coding-corrected nighttime light data provided by Bluhm and Krause (2022). All of the main conclusions remain robust with the corrected dataset. Table B1 replicates regressions in Table 1. The differences in coefficient magnitudes are negligible.

Table B2 reestimates the elasticities and the measurement-error distribution. The estimated parameters and the measured GDP misreporting remain stable. Notably, the measured GDP misreporting for China becomes smaller. One possible explanation is that correcting top-coding in bright regions such as Beijing and Shanghai raises measured nighttime light growth in China and therefore increases the implied measure of true economic growth.

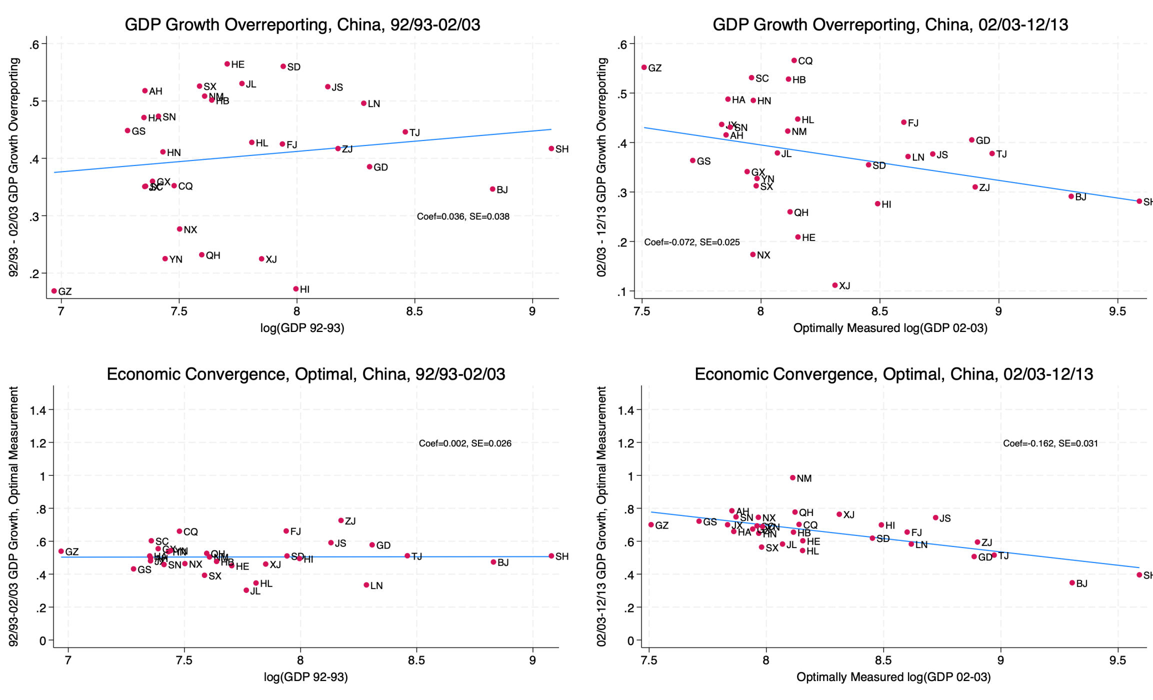
Figure B5 replicates Figure 3 using the top-coding-corrected data. The main patterns remain robust. The negative relationship between measured GDP overstatement and initial GDP remains, and the newly estimated annual convergence rate is 1.6%.

Table B1: Regression of Official GDP Growth on Growth of Nighttime Light and Electricity Consumption, Data Corrected for Top-Coding

	Growth in Official GDP					
	1992/93-2002/03			2002/03-2012/13		
	(1)	(2)	(3)	(4)	(5)	(6)
Nighttime Light Growth	0.292		0.211	0.329		0.235
	(0.098)		(0.117)	(0.062)		(0.073)
Electricity Consumption Growth		0.254	0.150		0.284	0.156
		(0.054)	(0.054)		(0.058)	(0.068)
Constant	0.061	0.107	0.046	0.173	0.236	0.167
	(0.043)	(0.028)	(0.043)	(0.039)	(0.032)	(0.039)
R^2	0.199	0.165	0.241	0.224	0.185	0.261

Note: Robust standard errors are reported in parentheses. The sample includes low- and middle-income countries whose statistical capacity score exceeds 3.5 out of 10. The sample size is 107 for 1992/93–2002/03 and 92 for 2002/03–2012/13.

Figure B5: Regional Convergence from Official Data and the Optimal Measure, and GDP Misreporting in Chinese Provinces, 1992–2013, Data Corrected for Top-Coding



Note: In the right-middle and right-bottom panels, the x-axis is the log of optimally measured GDP in 2002/03, calculated as GDP in 1992/93 multiplied by the constructed growth rates.

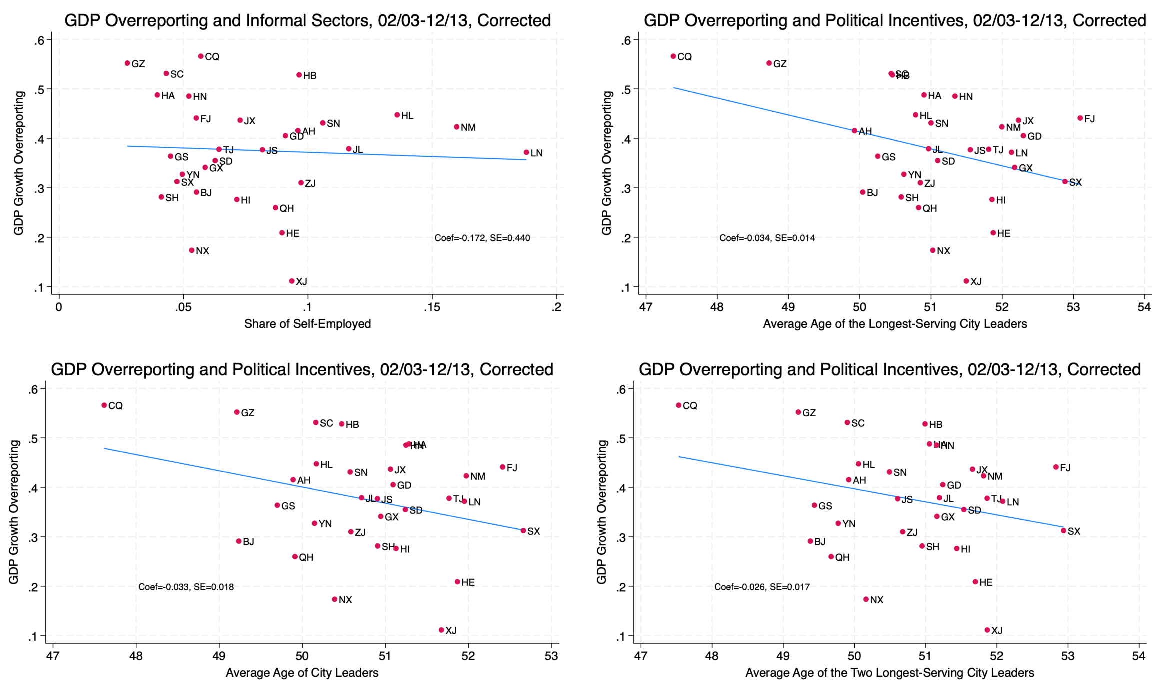
Table B2: Estimation Results: Data Corrected for Top-Coded

	1992/93–2002/03	2002/03–2012/13
Panel A. Estimated parameters		
α_1	1.781	1.954
	(0.419)	(0.481)
α_2	1.751	1.773
	(0.700)	(0.448)
$\sigma^2_{y^*}$	0.026	0.019
	(0.015)	(0.007)
$\sigma^2_{\varepsilon_y}$	0.045	0.032
	(0.011)	(0.009)
$\sigma^2_{\varepsilon_1}$	0.083	0.047
	(0.025)	(0.014)
$\sigma^2_{\varepsilon_2}$	0.101	0.058
	(0.031)	(0.014)
Panel B. Implied optimal weights		
ω_y	0.246	0.186
$\omega_1\alpha_1$	0.420	0.489
$\omega_2\alpha_2$	0.334	0.325
Panel C. GDP Misreporting of Selected Countries (percentage point, annually)		
China	3.5	3.0
India	1.7	1.0
Brazil	0.2	-0.8
South Africa	0.6	0.0

Note: Robust standard errors are reported in parentheses. The sample includes low- and middle-income countries whose statistical capacity score exceeds 3.5 out of 10. The sample size is 107 for 1992/93–2002/03 and 92 for 2002/03–2012/13. Panel C reports the annual percentage-point difference between official GDP growth and the optimal measure.

Figure B6 replicates Figures 4 and A3 using the top-coding-corrected data. The results remain similar. Measured GDP overstatement is not correlated with the share of self-employed workers and is negatively correlated with the age of local officials.

Figure B6: The Effects of Informal Sectors and Political Incentive on Measured GDP Misreporting, Data Corrected for Top-Coding



Note: In the left panel, the x-axis is the share of self-employed workers in total employment. In the right panel, the x-axis is the average age of the longest-serving city leaders, including party secretaries and mayors, within a province. In Figure A3, I replace the explanatory variable with the average age of all city leaders and the average age of the two longest-serving city leaders. The results remain robust. Data on local officials are compiled by Jiang (2018).

C Details of the Model in Section 3

This section provides details and proofs of the theoretical model in Section 3. The first order conditions with respect to K_{Git+1} and ψ_{it+1} can be given by Equations (C1) and (C2):

$$F(Y_{it+1}, \psi_{it+1}; Y_{it}) = -\frac{\chi}{\theta}\frac{\left(\frac{Y_{it+1}}{A_{it+1}}\right)^{\frac{1}{\theta}}}{\tau_y Y_{it} - \left(\frac{Y_{it+1}}{A_{it+1}}\right)^{\frac{1}{\theta}}}\frac{1}{Y_{it+1}} + \chi\rho\frac{\tau_y - T'(\psi_{it+1}Y_{it+1})\psi_{it+1}}{\tau_y Y_{it+1} - T(\psi_{it+1}Y_{it+1})} + \frac{1+\rho+\kappa}{Y_{it+1}} = 0 \tag{C1}$$

$$H(Y_{it+1}, \psi_{it+1}; Y_{it}) = -\chi\rho\frac{T'(\psi_{it+1}Y_{it+1})Y_{it+1}}{\tau_y Y_{it+1} - T(\psi_{it+1}Y_{it+1})} + \kappa\frac{1}{\psi_{it+1}} = 0 \tag{C2}$$

To simplify the notation, let $T(\cdot)$ represent $T(\psi_{it+1}Y_{it+1})$. Let F_x and H_x denote the partial derivatives of functions F and H with respect to the variable x. From the implicit function theorem and Cramer's Rule, we have

$$\frac{\partial Y_{it+1}}{\partial Y_{it}} = -\frac{F_{Y_{it}}H_{\psi_{it+1}}}{D}, \quad \frac{\partial \psi_{it+1}}{\partial Y_{it}} = \frac{F_{Y_{it}}H_{Y_{it+1}}}{D}$$

where $D = F_{Y_{it+1}}H_{\psi_{it+1}} - F_{\psi_{it+1}}H_{Y_{it+1}}$ is the Hessian determinant. I assume that the equilibrium is an interior local maximum so that $D > 0$.

Taking partial derivatives of H with respect to Y_{it+1} and ψ_{it+1} yields:

$$H_{\psi_{it+1}} = -\chi\rho\frac{T''(\cdot)Y_{it+1}^2(\tau_y Y_{it+1} - T(\cdot)) + (T'(\cdot)Y_{it+1})^2}{(\tau_y Y_{it+1} - T(\cdot))^2} - \frac{\kappa}{\psi_{it+1}^2} < 0$$

$$H_{Y_{it+1}} = -\chi\rho\frac{T''(\cdot)\psi_{it+1}Y_{it+1}(\tau_y Y_{it+1} - T) + T'(\cdot)(\psi_{it+1}Y_{it+1}T'(\cdot) - T(\cdot))}{(\tau_y Y_{it+1} - T(\cdot))^2}$$

Then, determine the sign of $F_{Y_{it}}$

$$F_{Y_{it}} = \frac{\chi}{\theta}\frac{\tau_y\left(\frac{Y_{it+1}}{A_{it+1}}\right)^{\frac{1}{\theta}}}{\left[\tau_y Y_{it} - \left(\frac{Y_{it+1}}{A_{it+1}}\right)^{\frac{1}{\theta}}\right]^2 Y_{it+1}} > 0$$

Therefore, we now have $\partial Y_{it+1}/\partial Y_{it} > 0$. Moreover, with $\theta < 1$, we have

$$0 < \frac{\partial \log Y_{it+1}}{\partial \log Y_{it}} < 1$$

To determine the sign of $H_{Y_{it+1}}$, we introduce a useful lemma:

Lemma 1. *Suppose a tax function $T(y)$ defined on $y > 0$ satisfies*

1. $\lim_{y\to 0} T(y) = 0$, *do not have to pay taxes when income is 0;*
2. $\lim_{y\to 0} T'(y)y = 0$

Then, we have

$$T'(y) \geq \frac{T(y)}{y} \quad \textit{if} \quad T''(y) \geq 0$$

with the equality holding if $T''(y) = 0$.

Proof. Define

$$g(y) = T'(y)y - T(y)$$

It is equivalent to show $g(y) \geq 0$. Then,

$$g'(y) = T''(y)y \geq 0 \quad \Rightarrow \quad g(y) \geq \lim_{y \to 0} g(y) = 0$$

with the equalities holding if $T''(y) = 0$. $\square$

Lemma 1 states the property of the linear tax scheme and the progressive tax scheme. If the tax scheme is progressive (linear), the marginal tax rate is greater than (equal to) the average tax rate, i.e.

$$T'(\cdot) \geq \frac{T(\cdot)}{\psi_{it+1} Y_{it+1}}$$

with the equality holding when $T''(\cdot) = 0$.

When the tax scheme is linear, $H_{Y_{it+1}} = 0$ and thereby $\partial \psi_{it+1} / \partial Y_{it} = 0$. When the tax scheme is progressive, $H_{Y_{it+1}} < 0$. Therefore, we can establish that $\partial \psi_{it+1} / \partial Y_{it} < 0$ under the progressive tax scheme.

Moreover, plugging Equation (C2) into (C1), the term including κ cancels out. Therefore, the relationship between ψ_{it+1} and κ is fully pinned down by Equation (C2). The first term is the marginal cost of overreproting and the second term is the marginal return which is increasing in κ. This yields Corollary 1.