Letting Old Data Speak: Local Cultural Traits in Qing China Grain Prices*

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Abstract: Detecting data manipulation in the Qing dynasty (1644-1912) reveals that such cheating behavior has persisted in modern China, for centuries. Qing prefectural officials were responsible for assembling local grain price data. We use the fact that grain prices are seasonal and cannot stay constant for a prolonged period as an indicator for Qing data manipulation. Using the instrumental variable approach, we find that Qing data quality reliably predicts data misreporting and exaggeration in modern China. We also identify that persistence was higher in more affluent places, like treaty port and coastal areas, where cheating can lead to higher rewards.

JEL codes: O13, N45, R11, D72.

Keywords: Culture, Historical Prices, Qing China, Principle-Agent.

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1 Introduction

The principal-agent problem arises from the delegation of authority and the misalignment of incentives. One central challenge facing the principal is the incomplete and asymmetric information about the agents' behavior. An optimal contracting view recognizes that the agents do not automatically seek to maximize the principal's value, and thus, it is important to provide agents with correct and adequate incentives. The understanding of the preference of the agents is crucial in providing such an optimal contract.

This article identifies cultural norms as powerful determinants of the severity of principal-agent problem. We find convincing empirical evidence that events and institutions in the past can influence norms and preferences today. Hence, ignoring such cultural information creates limitations on the optimal contract and prevents the contract from providing cost-effectively the incentives needed to align the interest between the principals and the agents.

Our analysis focuses on a specific type of principal-agent problem: data reporting from peripheral governments (the agents) to the central government (the principals) in China over centuries. In particular, we analyze the historical roots of data manipulation in modern China. We explore the long-term persistence of poor-quality data reporting using Qing Dynasty Grain Price Database (QGPD). The database provides prefectural-level grain price data of all major grain types at a monthly frequency from 1736 to 1911.[1]

We find that the quality of reported QGPD data varies across prefectures. As grain harvest is seasonal, if observed grain prices remain the same over a prolonged period, it is likely that the reported data are falsified. This type of problem is easily detected, and even the Qing emperors themselves had complained about such data manipulation (Chen, 1992; Chen and Wang, 2004). We apply McCrary (2008) method on QGPD to detect suspicious data and recidivating prefectures. Employing instrumental variable approach, we also find the persistence of such poor-quality data reporting in modern China, after more than half a century. Localities that had poor data quality in the Qing dynasty were also more likely to misreport GDP data in the 2000s and inflate the crop production data in the late 1950s that eventually led to the Great Famine.

How can the same form of behavior be found in the same location with different reporting officials decades apart? We hypothesize that culture can be important in explaining the transmission. If culture can reduce the moral cost of committing certain wrong-doings, we would expect culture to have an influence on data manipulation.[2] We show that the frequency of data manipulation in the Qing dynasty has a strong and significant correlation with Confucian values that show loyalty to the emperor and number of sages, who have values that are related to governance, but not significant to the values that show subordination to one's parents or husband. Under certain conditions, the long-term transmission of poor-quality data reporting strengthens. For example, localities with a

[1] Due to its comprehensiveness, the QGPD dataset is popular and is used by numerous studies in economics (see, for example, Li, 2000; Shiue, 2002; Keller and Shiue, 2007; Jia, 2014*b*; Gao and Lei, 2019; Bernhofen et al., 2020, among others).

[2] See Section 3.1 for a stylized model to fix our idea. The model predicts that number of data manipulation events in the past reduces the moral cost of data manipulation in the present and make a place with more cheating events in the past more likely to cheat in the present.

treaty port status show significantly higher persistence over the long term than other communities because the treaty ports have usually been more affluence (Jia, 2014*a*) and provide a higher incentive to cheat.

We choose China as our focus because of two unique salient features. First, modern China's political system gives the local officials incentives to achieve certain economic and social targets, and these targets are linked to their career promotion (Li and Zhou, 2005; Jia, Kudamatsu and Seim, 2015; Chen and Kung, 2019; Chen, Qiao and Zhu, 2021). This creates reasons for local officials to cheat (see Greenstone et al., 2022, for the case of air pollution). Second, the large size of China makes monitoring more difficult in some regions when compared to the others (Sng, 2014). This creates a large enough cross-prefecture variation in the Qing dynasty and allows us to draw inference on how poor-quality data reporting in the Qing dynasty connects with data manipulation in the present time.

This article contributes to the literature on the long-run effects of local events and institutions. Alesina and Ferrara (2005) finds that cultural and religious fragmentation is robustly associated with outcome variables such as civil wars, corruption, and public goods provision. Fernández and Fogli (2009) provide evidence that the fertility of migrants' children is affected by the migrants' countries of origin. Alesina, Giuliano and Nunn (2013) show that the historical use of agricultural plow affects the contemporaneous gender roles. Nunn and Wantchekon (2011) argue that the slave trade in Africa led to a permanently lower level of trust. Voigtländer and Voth (2012) find connection between medieval and modern anti-Semitism. These results are consistent with our finding that the persistence of poor-quality data reporting. Dalton and Leung (2014) argue that slaver trade created sex ratio imbalance and led to polygyny in western Africa today. Similar to Chen, Kung and Ma (2020), our work focuses on China and investigates the transmission of culture in time. We do not use a specific historical event or institution as the starting point of the analysis. Instead, we are looking for hints in behaviors (i.e., officials reporting questionable grain price data) and use that as a proxy of cultural traits. While it is not feasible to trace where those traits ultimately come from, our approach allows us to look at the long-term effects of culture by taking a "snapshot" of them at a particular point in history.

This paper also relates to the literature on data reliability issues. Henderson, Storeygard and Weil (2012) point out that there are problems with GDP statistics. Magee and Doces (2015) show that GDP manipulation is more severe in authoritarian regimes. Rawski (2001) and Chen et al. (2019) find evidence that accounts contain numerous inconsistencies. Greenstone et al. (2022) shows that air quality data was problematic. We focus on the data in QGPD and show that such data quality problems also happened in pre-modern China. Although QGPD has been widely used in the literature (see, for example, Li, 2000; Shiue, 2002; Keller and Shiue, 2007; Jia, 2014*b*; Gao and Lei, 2019), its reliability has rarely been discussed (except Bernhofen et al., 2020). In this study, we find that most of the grain price data are reliable and broadly reflect the impacts of wars, climate, geography, and market integration. However, we provide evidence that a non-negligible number of observations in the dataset are likely to be problematic as some observations did not change for a prolonged period.

Last but not least, the article also contributes to the understanding of the principal-agent problem in China. While most of the literature studies how officials respond to various promotion incentives (see, for example, Guo, 2009; Lichtenberg and Ding, 2009; Piotroski and Zhang, 2014; Wang, Zhang and Zhou, 2020), this study takes another approach and focuses on the cultural determinant of data manipulation. If culture can reduce the moral cost of committing certain wrong-doings, we would expect culture to have an influence on data manipulation.

The remaining part of the paper will be organized as follows: Section 2 that follows will discuss the historical background, data construction, and sample of this study. We will present a simple stylized model in Section 3 that fixes our idea. Section 4 will be our main methodology and result. Some of the mechanisms will be discussed in Section 5. And we conclude in Section 6.

2 Background, Data and Sample

We use data from two eras – the Qing period and the modern period (post-1949). Our measure of Qing data misreporting comes from Qing Dynasty Grain Price Database (QGPD), which provides prefectural-level grain price data of all major grain types over 170 years that spans most of the Qing dynasty. There is considerable variation in the extent of the data quality at the prefecture-level. We can therefore compare data quality in the Qing dynasty with similar reporting in the same location centuries later.

We follow Bai and Jia (2021) and Keller and Shiue (2007) and restrict our sample to only the China proper, which does not include, broadly speaking, Tibet, Xinjiang, Mongolia, and Manchuria.

2.1 Qing Grain Price Data Manipulation

The publicly available Qing Dynasty Grain Price Database (*Qingdai liangjia ziliao ku*, henceforth QGPD), initiated by Yeh-Chien Wang at Academia Sinica, contains grain prices at the prefecture level and monthly frequency during most of the Qing dynasty. Due to the close connection between food security and political stability, the Qing dynasty began to collect local grain price data in 1736 in order to better understand their variations across regions and over time. In each month, surveys were done multiple times in each county within a prefecture (there was no regulation on the number of surveys to be conducted, and the county-level records were mostly lost), and the highest and lowest prices for all available grain types in each prefecture were reported based on such observations. The data were then compiled at the province level before submitting to the central government. Each report, called a grain price checklist (*liangjia dan*), contains the highest and lowest price for each type of grain in each prefecture. The dataset spans 174 years from 1736 to 1911 and includes 339 prefectures which covers almost the whole kingdom as well as 42 grain types. For the rest of the paper, we denote $P^h_{i,j,m}$ as the high price of grain type j in prefecture i at time (month) m, and $P^l_{i,j,m}$ as the corresponding low price. To have a sense of how the data look like, we plot in Figure A1 the average grain price (in *fen*, which is equal to one hundredth of a tael, or *liang*) of each province over time.

The data submitted by the local governments were only for informational purposes, allowing the central government to have a better sense of how the economy was doing.[3] Several reporting mechanisms were created to guarantee the reliability of the data. For instance, irregular reports were used to check the accuracy of the record in the regular grain price reports. Nonetheless, as we will show, questionable reports were not uncommon. Occasionally, the emperor did notice the data quality issue, and reproofs were issued against some obviously unreliable data (see Chen, 1992). Figure A2 plots price observations of wheat at two prefectures to demonstrate the variations in data quality. The first panel shows a prefecture with grain prices remaining constant for more than 6 months. The second panel presents observations of a prefecture without such feature.

Why did officials produce such questionable data? We think there are at least two reasons. The first is plain irresponsibility, as collecting and verifying the grain data was costly. Officials needed to be sent to local regions to do the survey, and those who were trying to shirk might just copy from old data or use other shortcuts. The second reason is strategic, as there are records that show emperors approving aid to regions that reported high grain prices during or after a period of severe bad weather.[4] In either case, the central government (the principal), that originally delegated the grain price reporting to the local governments (the agents), could not successfully extract information due to imperfect monitoring. This led to a classical principal-agent problem.

2.1.1 Detecting Qing Grain Price Data Manipulation

We follow the tradition in the literature (Chen, 1992; Chen and Wang, 2004) and propose a measure of zero price changes in grain price data. We use McCrary's (2008) test to detect zero price changes in grain price data. McCrary's test detects manipulation related to continuity of the running variable density function and has been primarily employed in studies using regression discontinuity designs.[5] In this approach, we first construct the distribution of 6-month price change by pooling both high and low prices and of all grains types together for each prefecture.[6] Then, we apply the McCrary's test on the discontinuity of this distribution at zero, which corresponds to zero price changes. Under the null hypothesis, the distribution of price change should be smooth. The following Figure 1 illustrates the example of two prefectures, Yongzhou and Liuzhou. The histogram density represents the likelihood of the changes in the grain price. We can see that the distribution of price change in Liuzhou is smoother than that in Yongzhou, because the former does not experience a jump in density in cutoff, which corresponds to the zero price change.

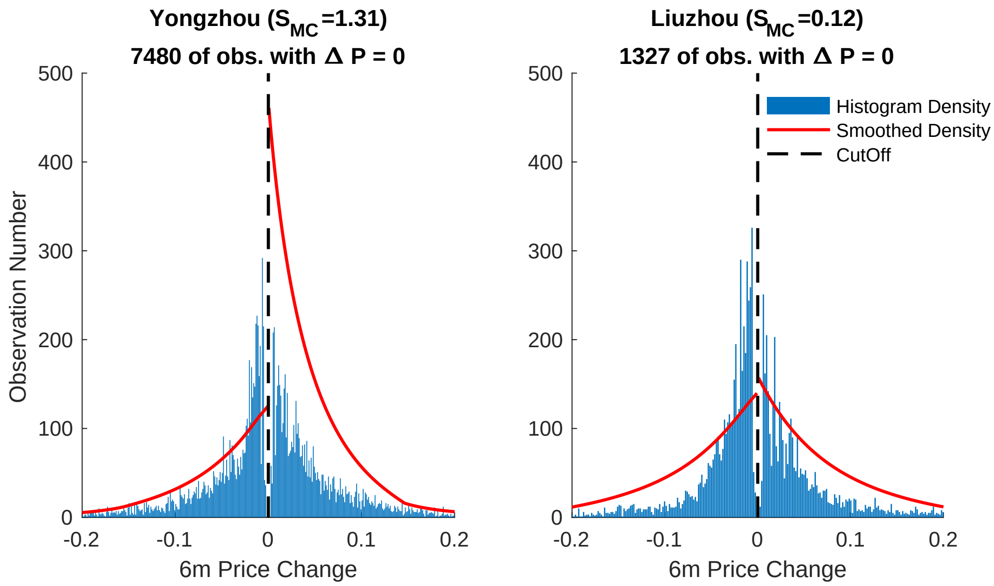
McCrary test statistics (S_{MC}) can be either positive or negative depending on which side of the

[3] The major source of tax income for the Qing dynasty came from land and poll taxes ("ti-ting") and depended on land size and fertility and the number of laborers, but not the production level. See Hsu (2000).

[4] For example, in the twentieth-first year of his reign (1895), emperor Guangxu commented on the area near the current Beizhen in northeast China: "I learned that the grain price in that area is exorbitant, and people have a hard time getting fed. I feel pity for them and have asked Yu Lu to find out what happened. To alleviate the plight of the people, taxes are forgiven and grain donation is initiated there." (Authors' translation from the Factual Record Of Qing Dynasty).

[5] McCrary's test first estimates local linear regressions of the density separately on either side of the cutoff and then implements a Wald test of the null hypothesis that there is no discontinuity. This test has been applied by numerous papers in economics on data manipulation (such as Fisman and Wang, 2017; Douglas and Xia, 2017).

[6] We choose six months as our baseline analysis because grain harvest is seasonal, and the 6-month interval is reasonable in capturing such seasonality.



Note: the zero spike is removed from the plot for better illustration. Number of zero price change observations is presented in the sub-figure title.

Figure 1: Example of McCrary's Test on Grain Price

distribution is denser. Since the extent of discontinuity at zero is our focus, we do not distinguish whether negative or positive price changes are more likely. Thus, we take the absolute value of the estimate. To use our example in Figure 1, the absolute value of the McCrary test statistics is higher in Yongzhou prefecture than that in Liuzhou prefecture. We use McCrary test statistics to define the measure such that a higher value indicates better quality. Therefore, -1 is multiplied by the absolute value of the McCrary test statistics to create the final quality measure (DQ_{MC}):[7]

$$DQ_{MC,i} = -1 \times |S_{MC,i}|$$

The lower is this measure, the lower is data quality.

2.2 Modern Data Manipulation

To connect the measures with modern data, we match the Qing prefectures to the modern administrative regions using the geographical crosswalks method adopted by Hornbeck (2010) and Eckerty

[7]The null is rejected for most prefectures, but our focus is not on the rejection by the test score. At 5% level, we have 3% of prefectures for which the null is not rejected. Thus, one cannot reject the null hypothesis that the distribution is continuous at zero for these locations. We choose to include these types of estimates because their test statistics are indeed close to zero. Alternatively, we can treat these test statistics as exactly zero. Our results are not affected much by this choice. Also, two prefectures are outliers with extremely high McCrary test statistics. They are Qin Zhou and Ya Zhou. We exclude these two locations in this measure, and the results are similar with or without the outliers.

et al. (2020).[8] We intersect Qing and modern maps covering the same territory, and we choose to keep the unit of analysis at the Qing prefecture-level. For example, let's say a Qing prefecture covers two prefectures in modern China, with 70% of area coming from the first and 30% coming from the second. The quality measure in that Qing prefecture is then used to explain 70% of the first modern prefecture and 30% of the second.[9] In what follows, we will discuss the two broad types of data manipulation.

2.2.1 GDP Manipulation

We focus on two measures of GDP manipulation. The first one is due to the GDP targeting. Modern Chinese government sets economic targets at all levels of territory administration, and upper-level officials convey the importance of economic growth and incentivize tournaments through these targets. One can interpret good target attainment as a signal of competent or conscientious local officials. Using the data from Li et al. (2019), we instead construct a bunching index at the prefecture level by calculating the absolute percentile deviation of the actual output from the targeted output from 2003 to 2014. According to Lyu et al. (2018), local growth data show a pattern that is highly suggestive of data manipulation: few observations have growth rates that are slightly below the target, and there is a bunching of observations near the point of exactly meeting the growth target. Lyu et al. (2018) suggest that the data are produced with "both paper-based and real-activity-based GDP management", meaning that officials manipulate the data directly and use tools like public spending to move the numbers in the preferred direction. Following Lyu et al. (2018), we construct a bunching index that equals 1 whenever the realized GDP growth exactly matches the target GDP growth or exceeds the targeted level by less than 0.4% of the target percentile.[10] Then, we calculate the frequency of the bunching index equals one for each prefecture.

The second measure is derived from using tools developed in Henderson, Storeygard and Weil (2012), that use the growth of the night light data to detect any discrepancy in night light and GDP growth. We combine light data (recorded by satellites from outer space) from the DMSP-OLS Nighttime Lights Time Series (`https://eogdata.mines.edu/products/dmsp/`) with prefecture-level GDP from Li et al. (2019) to detect any discrepancy. Following Henderson, Storeygard and Weil (2012), we regress the log level of GDP of each prefecture on a log measure of observed light,

[8] Qing prefecture GIS data is from CHGIS (Fairbank Center for Chinese Studies of Harvard University and the Center for Historical Geographical Studies at Fudan University, 2016). Modern county-level GIS data is from Hijmans (2015), and modern prefecture-level GIS data is from the Centre for Humanitarian Data (established by the United Nations Office for the Coordination of Humanitarian Affairs).

[9] It is possible to weight the data in the opposite direction. We can keep modern prefectures (or other levels) as the unit of analysis instead, and the quality measure for each prefecture will be a weighted sum from different Qing prefectures. But we would like to argue that this approach is not suitable for our purpose. If quality measure indeed reflects persistent cultural characteristics, such a matching procedure imposes the strong assumption that they are cardinal or that they can be added and subtracted. For example, if the modern prefecture is equally split in the area into two Qing prefectures, we will then impose the restriction that the modern prefecture is influenced by the average of the two sources of cultural characteristics. We do not think characteristics like Confucian values can be summed up like that, and hence we will keep Qing prefectures as the unit of analysis. On the contrary, the modern measures investigated in this section are cardinal numbers and can be averaged.

[10] Increasing this threshold value does not change the results much, but reducing it further will give us too few observations that satisfy the threshold.

prefecture fixed effects, and year fixed effects. The regression tells us how economic growth is related to lights on average, and for each prefecture, we then calculate the frequency of having a positive residual, i.e., the reported GDP is too high relative to the light measure.

2.2.2 Great Famine and Production Exaggeration

The Chinese Great Famine (1959-1961) led to 16.5 to 45 million unnatural deaths, according to historical evidence. The severity of famine varies both within and across provinces, and we follow the approach of Meng, Qian and Yared (2015) and use the local birth cohort size to proxy the famine severity. First, we follow the original study and regress the severity of famine on a list of controls.[11] We focus on the unexplained variations in famine severity that cannot be explained by the controls.

The connection between famine severity and data manipulation warrants more discussion. According to previous studies (Li and Yang, 2005; Meng, Qian and Yared, 2015, see, for example,), the Great Famine can be explained by a rigid procurement system. Meng, Qian and Yared (2015) argue that some local bureaucrats historically exaggerated production, which led the central government to over-estimate the expected agricultural production. Such bias would exacerbate through the rigid procurement system and reduce aggregate consumption. This is consistent with their finding that rural mortality rates were *positively* correlated with per capita food production, which was only observed during the famine era. So, the severity of the famine can be a good indicator of exaggerated production, a form of data manipulation, controlling for other observable (e.g., weather).

2.3 Cultural Measure

Following Kung and Ma (2014), we have hand-collected data on the number of chaste women *(lienü)* and sages *(xian)*, together with filial piety *(xiao)* and loyalty *(zhong)* and use them as our proxies of Confucius value. These virtuous quality were honored in Confucian norms.

For example, chaste women were usually widows who vowed not to remarry or even committed suicide to preserve fidelity and loyalty to their late husbands, in accordance with the Confucian thinking of subordination and obedience *(gang)*. Chaste women were nominated by the local gentries, and the candidates were scrutinized by the government and confirmed by the court. Since chaste women exemplified laudable conduct and were greatly honored in their local communities, their names were recorded in local gazetteers and eventually compiled into Complete Library in Four Sections *(Siku Quanshu)*. The dataset is digitized using Siku Quanshu Publishing Committee (2005), and it consists of 18 provinces.[12] Other forms of virtuous quality were also recorded in local gazetteers and eventually compiled into Complete Library in Four Sections.

[11] They include spring temperature, spring rainfall, grain suitability, distance to a railroad, distance to a big city, and province fixed effects.

[12] They are Zhili, Jiangsu, Anhui, Zhejiang, Jiangxi, Fujian, Henan, Shandong, Shanxi, Hubei, Hunan, Shaanxi, Gansu, Sichuan, Guangdong, Guangxi, Yunnan, Guizhou.

2.4 Other Controls

Weather data at annual frequency come from the Historical Data of Droughts and Floods of the Past 500 Years in China (*Zhongguo Hanlao Wubai Nian*), which includes 1470-1992 weather data from 120 weather observation stations across China. The weather index spans from 1 (indicating a drought) to 5 (indicating a flood). In a particular year, given the geolocation data of prefecture n, we match it to the nearest observation station in the weather data that recorded a valid weather index. Further, as a cross-sectional measure, we calculate the average adverse weather in each prefecture.

War data are based on the Time Table of Wars in Chinese History (*Zhonguo Lidai Zhanzheng Nianbiao*) from which we collect by hand the exact time (at the monthly frequency) and location (at prefecture-level) of each war. We then construct a panel of war index as follows. First, we generate a war dummy whenever the observation is located within the "center" of the war. If the record only shows the location of war at the provincial level, then all prefectures in that province will have the dummy variable equal to one. If the record shows the location of war at the prefecture or lower level, all prefectures within a 200 km radius from the war location have the dummy variable equal to one. Finally, as a cross-sectional measure, we calculate the frequency of war in each prefecture.

Geographic controls include the average slope, latitude, and longitude of a prefecture. These controls are related to the farming climate facing the farmer and potentially have an effect on the reported grain price data quality.

2.5 Data Overview

Table 1 gives an overview of the key variables. Table A1 shows the point-wise correlation among the Qing data quality measures and data manipulation indices in the modern time.

Qing data quality is negatively and significantly correlated with all indices, except for GDP bunching. It is worth pointing out that the correlations of modern data manipulation indices are not significant, albeit they are positively correlated. This shows that the data manipulation indices capture a different aspect of data misreporting. In the following analysis, we will normalize DQ_{MC}, GDP light, GDP bunching, and famine severity into standard normal measures for better interpretation.

3 Mechanism

This section is divided into two parts. The first is to highlight a stylized model and to fix the idea of this project. The second part will discuss some anecdotal historical facts to support the prediction from the stylized model.

3.1 Stylized Model

There is a continuum of agents (he) that differ by their private benefit b derived from cheating. The distribution of b follows uniform distribution with support $[0, \bar{b}]$. The total benefit that an agent

Table 1: Summary Statistics

Variables	Mean	S.D.	Obs.
A: Qing Data Quality Measure			
DQ_{MC}	-1.117	0.495	317
B: Modern Data Manipulation Index			
GDP Light	0.549	0.283	297
GDP bunching	0.003	0.030	298
Famine severity	0.003	0.134	266
C: Instrument			
Inverse Distance to Provincial Capital	6.880	7.763	280
Density of Sages	0.066	0.164	263
D: Other Control			
Average Climate	1.046	0.127	300
Average War Frequency	0.028	0.014	300
Average Slope	88.655	3.586	300
Latitude	30.919	5.447	300
Longitude	111.835	6.188	300

will receive from cheating is $\zeta b + y$, where y is the agent's salary, which is assumed to be the same among agents. ζ is the coefficient that captures the economic performance of a location, and if a location is with higher ζ (more affluent), then the cheating agent will create greater benefit.

The moral cost of cheating is τ, and the principal (she) will monitor the agent with probability $(1-\theta)$. To simplify the exposition, we assume that when the principal monitors, there is a measure one chance that she detects the cheating. When the agent is detected cheating, he will end up with 0 net benefits. So, the expected net benefit from cheating is then $\theta(\zeta b + y - \tau)$, and that from not cheating is simply the salary y.

It is straightforward to show that there exists a cutoff $b^* = \frac{1}{\zeta}\left(\frac{1-\theta}{\theta}y + \tau\right)$ which for all $b > b^*$, agents will cheat and for all $b < b^*$, agents will not cheat. So, the mass of agents who do not cheat is $\frac{b^*}{\bar{b}}$ and the mass of agents who cheat is $\frac{\bar{b}-b^*}{\bar{b}}$

So far, the stylized model outlined is the same as in the literature. Imagine that the moral cost of cheating is in the form of $\tau(\bar{b}-b^*_{-1})$ where $\bar{b}-b^*_{-1}$ is proportional to the mass of agents who cheat (those with high enough idiosyncratic benefit) in the previous period. We assume that $\tau(.) < 0$ so that more agents who cheated in the past reduce the moral cost of cheating in the current period. Thus, we will have the following two testable hypotheses from this stylized model:

1. The mass of agents who cheat $\bar{b} - b^*$ is decreasing in the monitoring probability $(1-\theta)$ but is increasing in the scale of benefit ζ

2. The more previous cheating, or high $\bar{b} - b^*_{-1}$, the lower the moral cost of cheating τ and hence more cheating in the current period

So, this stylized model gives us some insight about how historical events affect current officials' behavior: the events happened in the past, conditional on sufficient number of people participated in the events, reduce the moral cost and induce officials to make decision that they would not have made should the previous events not happen. This effect is also stronger when the locality that the official served is more affluent (e.g. coastal and treaty port prefectures) and face less monitoring probability (e.g. distant prefectures from capital).

3.2 Local Officials and Political Selection

While hypothesis 1 is standard in the literature, we explain in this section why hypothesis 2 may also hold in the real world. In particular, we argue the mechanism and historical facts of which data manipulation can be transmitted through time.

To begin, we need to clarify who the officials were that collected the grain price data, and how their cultural characteristics could persist for a long time. Our argument has two steps. First, we will show evidence that grain price collection, on top of other administrative tasks, was undertaken by a group of local clerks knowledgeable of and well-connected with the region. Second, due to their power of recommending and even selecting recruits, local officials were to retain like-minded people in the government, and that created the persistent characteristics that we have shown.

Chu (1962) and Reed (2000) describe how local (prefecture and lower levels) governments worked in the Qing dynasty, and both emphasize the crucial roles of clerks, government runners, personal servants, and private secretaries. Zhou (2016) also points to the separation of local magistrates and personnel (*guanli fentu*). Due to the law of "avoidance" (*hui-pi*), a magistrate "was permitted to hold office neither in his native province nor in a neighboring province within 500 li of his home town." (Chu, 1962, page 21) While personal servants and private secretaries were close to the magistrate and usually just followed him around the country, clerks and runners were natives.

Clerks were responsible for drafting documents, preparing reports, issuing warrants, keeping tax records, and filing documents for upper-level officials. Based on a detailed study of the Bao county yamen, Reed (2000) mentions that clerks took care of "management and collection of all land and deed taxes, special levies, provisions for orphans and the indigent, population counts, *baojia* registers and changes of all *baojia* personnel, and commodity price lists and weather reports." Chu (1962, Appendix) also mentions that clerks charged a fee for making grain price reports (page 216 n44). It is clear that the grain price data used in this paper originally came from the effort or lack thereof of the clerks, and it is reasonable to assume that similar quality issues existed for other data.

It is the head clerk but not the magistrate who was responsible for their recruitment. "Controlling as he did the assignment of cases, the disbursal of fees, the disciplining of subordinate clerks, and the recruitment of new clerks, the head clerk's position was one of substantial power." (Reed, 2000, page 64) There is evidence that clerks tried to keep like-minded people as colleagues and particularly disliked having an outsider as the head clerk. Citing a petition by nine regular clerks in the Bao county, Reed (2000) concludes that "the division's regular clerks not only rejected the intrusion of an untrained outsider but also they insisted that the selection of a new head clerk be restricted to those regular clerks already serving in their own division. In such instances, the issue was one of both the technical competence of the individual in question and also his familiarity and interpersonal relationships within the division." Similar barriers to entry existed for other low-level official posts.

During the Qing dynasty, we had a local bureaucracy that was responsible for most day-to-day administrative tasks and also had substantial power in controlling its composition. Such a setting fits into the model of Acemoglu, Egorov and Sonin (2010) which provides part of the explanation to our results. If the officials have some veto power and control of the hiring process, then highly inefficient and incompetent may resist changes and reforms and persist over time. After the fall of the Qing dynasty, both the Republican and Communist governments had increased the number of local officials and tightened the control of the central government, but as described in Huang (2014), some elements of the semi-formal governance by quasi officials persisted, and it is reasonable to argue that part of the influence of local veto power survived the drastic political changes. It is analogous to what Xu (2011) describes as "regionally decentralized authoritarian system". In addition, the "avoidance" (*hui-pi*) system is officially no longer in place after the fall of the Qing dynasty, making it more likely for local people to have more influence on local administration.

4 Baseline Result

In this section, we present our main results. In some prefectures, Qing officials were more likely to misreport grain price data. We argue that the data quality in the Qing dynasty at least partly reflects pre-modern attitude toward data manipulation. Similarly, the tournament system in modern China made data manipulation more profitable for official promotion. We demonstrate that across a range of indicators, prefectures with low Qing data quality also engaged in more data manipulation in modern times.

4.1 Empirical Strategy and Result

The main regression that we are interested in is how the Qing period data quality (which captures pre-modern attitude toward data manipulation) affects data manipulation in modern China. For each prefecture i, our cross-sectional analysis is conducted as:

$$DM_i = \alpha_0 + \alpha_1 DQ_{MC,i} + \alpha \mathbf{X}_i + \epsilon_i \tag{1}$$

where DM_i represents the various proxies for data manipulation in the modern China at prefecture level, and $\mathbf{X}_i$ is a vector of control variables. Our main control variables are average climate, war frequency, and other geographical controls like average slope, latitude and longitude of the prefecture. We cluster our error ϵ_i to province level.

To circumvent the measurement errors and endogeneity concerns, we also adopt an IV strategy to identify the effect of Qing period data manipulation on the modern outcome. In the baseline analysis, we use the inverse of distance to provincial capital $Dist_i^{-1}$ and province fixed effect as instruments to predict the data quality in the Qing period.[13] The choice of instrument is consistent with Steinwender (2018) and with the gravity equation from the trade literature (see, for example, Anderson, 2011) that information (and trade) flow is inversely related to distance. The first-stage and second-stage specifications are as follows:

$$DQ_{MC,i} = \beta_0 + \beta_1 Dist_i^{-1} + \beta_2 \delta_p + \beta \mathbf{X}_i + \epsilon_i \tag{2}$$

and

$$DM_i = \gamma_0 + \gamma_1 \widehat{DQ}_{MC,i} + \gamma \mathbf{X}_i + \epsilon_i \tag{3}$$

where $\mathbf{X}_i$ includes all the controls from equation (1).

Table 2: The Impact of Qing Data Quality on Data Manipulation

Dependent Variables:	GDP Light		GDP Bunching		Famine Severity		First Principal Component	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: OLS								
DQ_{MC}	-0.187**	-0.185**	-0.098*	-0.094**	-0.184***	-0.223***	-0.278***	-0.325***
	(0.075)	(0.070)	(0.047)	(0.044)	(0.053)	(0.056)	(0.068)	(0.065)
Panel B: 2SLS								
$\widehat{DQ}_{MC}$		-0.341***		-0.095*		-0.179***		-0.382***
		(0.083)		(0.052)		(0.051)		(0.056)
Control	N	Y	N	Y	N	Y	N	Y
N	269	269	270	270	240	240	238	238
R-Squared	0.03	0.06	0.01	0.05	0.03	0.05	0.06	0.09

Notes: All regression run at the prefecture level. Standard errors in parentheses, clustered at the province level. Modern prefecture is mapped to the Qing prefecture boundary. The controls include average climate, average war frequency, average slope, latitude and longitude of the prefecture. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 2 reports the baseline result. All the coefficients are negative and significant, indicating that the higher data quality in the Qing dynasty reduces the problem of data manipulation in the modern period. The effect is also significant economically. For example, the increase in the data quality by one standard deviation in the Qing dynasty reduce the chance of GDP misreporting by 0.34 standard deviation, the chance of GDP bunching by 0.10 standard deviation, and the famine severity by 0.18 standard deviation.

The first stage is significant, and the inclusion of inverse distance to provincial capital and province fixed effects lead all first-stage F-statistics well above 50, indicating that the weak instrument problem is not a big concern. We also follow Kung and Ma (2014) and use the density of sages in the early Qing era (the number of sages in the pre-Qing period divided by the population in early Qing, the year 1776), and the coefficients estimated are similar to that in Table 2 only that the counterpart coefficient to column (4) will be insignificant.[14]

Do our measures of data misreporting in modern China capture a broader, underlying pattern of

[13] We also follow Kung and Ma (2014) and use the density of sages as instruments, the result is similar. We will come back to this point later in Section 5.2.

[14] The reason that we do not use this measure as our main analysis is because there are many missing data, and we can just collect data for around 70 prefectures. We will go back to this discussion in Section 5.2.

attitudes towards data manipulation, or are they just isolated phenomena that occasionally coincide with pre-modern data misreporting? Following the method of Voigtländer and Voth (2012), we obtain the first principal component from all three modern China outcome variables. We then calculate the first principal component for the sample we have. All variables have positive factor loadings, suggesting that our indicators capture an underlying attitude towards data manipulation. The first principal component explains 37% of the sample variance.

Next, we employ the principal component as a dependent variable, and we investigate the effect of Qing period data misreporting on the first principal component. The result is presented in Table 2 columns (7) and (8). We obtain a strong and significant result for Qing data misreporting. According to the estimates, the effect is large. Deterioration of Qing period data quality by one standard deviation increases the dependent variable by 0.28-0.38 standard deviation.

Can distance to the provincial capital be a valid instrument in the analysis? Can the result be driven by the fact that the distant prefectures remained far away from the provincial capital and have been poor and castaway prefectures that no one cares? It is true that most of the provincial capital have not been changed since the Qing dynasty, but if we focus our subsample just to the those with provincial capital change,[15] the increase in 1 standard deviation of the data quality in the Qing dynasty will lead to -0.28 reduction ($p < 0.01$) in the severity of data misreporting in current data manipulation using the IV regression.

Although it is true that most of the provincial capitals have not been changed in the last 400 years, the economic conditions among them are very different. For example, Jiangnan cities such as Suzhou has lost its prominent position to Shanghai after the Taiping Rebellion (Yue, 2006). So, it is very hard to believe that the economic center have not changed. Figure A3 illustrates the population growth rate (proxy for economic prosperity) in early and late Qing period and their correlation is not significant.

4.2 Robustness

In the baseline analysis, we use all the available crop types for the construction of DQ_{MC}. However, some types might not be actively traded in the market, and might experience a prolonged period of missing data. So, the government officials simply copied the previous period's price data or kept it missing. To circumvent this problem, we also construct an alternative measure that uses major grain types for northern and southern China separately. For the prefectures in the north, we construct data quality using price data of wheat, millet, and sorghum (the most popular grain type in north China in the Qing dynasty, according to Li (2000)). For the prefectures in the south, we construct data quality using price data of three different quality types of rice. The results are reported in Table A2, and all the coefficients are negative and significant.

In addition, the choice of 6-month as a threshold for price change also does not change our main result. To show this, we construct the distribution of 3-month price change by pooling both high and low prices and of all grains types together for each prefecture.[16] Then, we apply the McCrary's

[15] They are Anhui, Guangxi, Henan, and Zhili (now Hebei, Beijing and Tianjin).

[16] Our original intention to choose six months as our threshold is because grain harvest is seasonal and 6-month

test on the discontinuity of this distribution at zero. The regression coefficients are shown in Table A3, and the main result stay broadly the same.

5 Origins of Qing Data Misreporting

Our result suggests a high degree of persistence in terms of attitude towards data manipulation at the local level. In this section, we explore two questions: What factors explain the Qing grain price misreporting, and what affects the cultural transmission of data manipulation?

5.1 Persistence of Data Quality Measure

Before we get into the explanation of data quality, it is instructive to look at the persistence of data quality during the Qing dynasty. Since DQ_{MC} does not have a time dimension, we construct an alternative but analogous measure $DQ_{const,it}$, which detects the frequency of price invariant within the 6-month interval.[17]

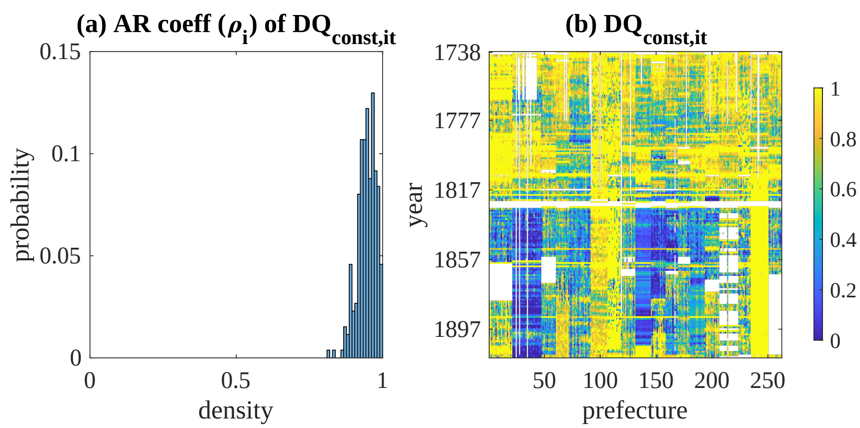


Figure 2: Persistence of Data Quality

We run the following AR(1) time series regression and report $\hat{\rho}_i$ for each prefecture i.

$$DQ_{const,it} = \rho_i DQ_{const,it-1} + \epsilon_{it} \tag{5}$$

interval is reasonable in capturing such seasonality.

[17]To be precious, we first construct a monthly data quality index measure using the frequency of grain price observations with an equal or larger than 6-month duration as follows:

$$DQ_{const,im} = 1 - \frac{1}{|J^i|} \sum_{j \in J^i} \frac{\not\Delta\,(P^h_{i,j,m}) + \not\Delta\,(P^l_{i,j,m})}{2}, \tag{4}$$

where $\not\Delta\,(P_{i,j,m}) = 1$ if $P_{i,j,m}$ is within a sequence of unchanged price for equals to 6 months, and $P_{i,j,m}$ is not the first observation of the sequence. J^i is the set of grain types reported in prefecture i, and $|J^i|$ is the cardinality of that set. Then, we construct $DQ_{const,it}$ as the annual average of $DQ_{const,im}$.

The result is plotted in Figure 2. From panel (a) of Figure 2, it can be seen that the persistence of the data quality measures is high, and some even show near-perfect auto-correlation. Panel (b) of Figure 2 shows that there are huge temporal and cross-sectional variations of $DQ_{const,it}$.[18]

5.2 Connection with Culture

In this part, we follow Kung and Ma (2014) and use the population density of people with virtuous qualities in a prefecture at the beginning of the Qing dynasty to proxy for Confucianism at the local level. Although all virtues are teachings from the Confucian thinking of subordination and obedience *(gang)*, their targets are quite different. *Xian* is the highest quality of Confucian thinking, and its quality is closed to a benevolent ruler who aligns his own interest with his object. *Zhong*, *xiao* and *lienü* are qualities that show subordination or loyalty towards the emperor, parents and husband, respectively.[19]

Table 3: Confucius Value and Data Quality

	Confucius Value							
	Sage (Xian)		Loyalty (Zhong)		Filial Piety (Xiao)		Chaste Women (Lienü)	
DQ_{MC}	0.486***	0.464***	0.328***	0.351***	0.177	0.154	0.020	0.016
	(0.092)	(0.105)	(0.085)	(0.084)	(0.153)	(0.170)	(0.021)	(0.020)
Provincial FE	Y	Y	Y	Y	Y	Y	Y	Y
Control	N	Y	N	Y	N	Y	N	Y
N	261	261	261	261	261	261	259	259
R-squared	0.82	0.82	0.81	0.82	0.81	0.82	0.81	0.81

Notes: All regression run at the prefecture level. Standard errors in parentheses, clustered at the province level. Confucius Value is defined as number of respective number before the Qing dynasty divided by the number of population in the year 1776. The controls include average climate, average war frequency, average slope, latitude and longitude of the prefecture. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

The correlations between data quality in the Qing dynasty and different qualities of Confucius value are positive, which shows the Confucius value has a positive effect on data quality. However, the coefficients are only significant for *xian* and *zhong*. This is intuitive since the other two qualities, *xiao* and *lienü*, are qualities that show subordination and loyalty to one's parents and husband. These two qualities have little to do with being a benevolent ruler. So, we show that the data quality measure was correlated with some aspects of Confucian values that are related to governance.

The interpretation of Table 3 aligns with our stylized model that all agents want to cheat as it will reduce their effort (or they derive some benefit from cheating). However, at the same time, they also faced certain moral cost that impede them from cheating. These moral costs are stronger in areas with larger Confucius influence since the teaching admonishes people to be righteous and benevolent. So, the data misreporting was less in area with larger Confucius influence.

[18] It is also obvious that there is a worsening of data persistence around the year 1820, which was the Daoguang period. We will discuss this later in this section.

[19] We follow the steps in Voigtländer and Voth (2012) to expand our samples by imputing places with no records as 0. This is reasonable since the lack of such records meant that the officials or citizens in that area were not interested in the virtuous qualities, which means that such qualities were less likely to affect the people there.

Table 4: Treaty Port Status and Coastal Proximity, 2SLS

	GDP Light (1)	GDP Bunching (2)	Famine Severity (3)	First Principal Component (4)
Panel A: Baseline	-0.341***	-0.095*	-0.179***	-0.382***
	(0.083)	(0.052)	(0.051)	(0.056)
N	269	270	240	238
Panel B: Treaty Port	-0.389***	-0.287**	-0.264**	-0.535***
	(0.201)	(0.130)	(0.125)	(0.109)
N	50	50	42	42
Panel C: Coastal	-0.808***	-0.231	-0.146	-0.612**
	(0.305)	(0.330)	(0.148)	(0.308)
N	36	36	31	31
Controls	Y	Y	Y	Y

Notes: All IV regression run at the prefecture level and only the second stage is reported. Standard errors in parentheses, clustered at the province level. Treaty port status is from Jia (2014*a*) and coastal region is defined if any boundary of the prefecture touches the sea. The controls include average climate, average war frequency, average slope, latitude and longitude of the prefecture. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

5.3 When did Transmission Amplify?

How do we make sense of the persistence of attitude towards data manipulation over centuries? To understand why persistence exists, we examine the conditions that affect it. In this part, we explore three factors, treaty port status, proximity to coastal regions, and time.

5.3.1 Treaty Port and Coastal

The transmission of culture is positively correlated with the benefit derived from cheating. As the treaty port area and the coastal areas are the focal point of development (see Jia, 2014*a*, for evidence that treaty port status also predicts modern growth), the officials working in such areas might have a higher incentive to misreport data to increase their chance of promotion. So, keeping the previous level of data manipulation constant, the higher the benefit of data manipulation, the more likely that one will cheat. This increases the persistence of data misreporting.

It can be seen from Table 4 that all the coefficients are negative, and most of them are significant. This shows that better Qing data quality leads to worse modern data manipulation. Moreover, it is also obvious that the coefficients from the subsample with treaty port and coastal status tend to have larger coefficients in absolute terms. This shows that the effect of Qing data quality on modern data manipulation is more persistent and exert a stronger effect on the prefectures with treaty port status and are in the coastal area, which has been more affluent.

The exercise here shows that on top of the current benefit generated from cheating, the past local experience is also important in determining the severity and the persistence of cheating.

Table 5: Pre- and Post- Daoguang Analysis

Panel A: Data Manipulation (2SLS)	GDP Light	GDP Bunching	Famine Severity	First Principal Component
	(1)	(2)	(3)	(4)
Pre-Daoguang	0.014	-0.068	-0.119	-0.143
	(0.133)	(0.112)	(0.093)	(0.116)
Post-Daoguang	-0.310***	-0.055	-0.149**	-0.325***
	(0.076)	(0.089)	(0.062)	(0.085)
N	243	244	220	218
Panel B: Confucius Value (OLS)	Sage (Xian)		Loyalty (Zhong)	
Pre-Daoguang	1.095***	1.204***	0.456***	0.624***
	(0.269)	(0.383)	(0.150)	(0.211)
Post-Daoguang	0.633***	0.596***	0.161	0.158
	(0.093)	(0.137)	(0.097)	(0.111)
N	259	259	259	259
Controls	N	Y	N	Y

Notes: All IV regression run at the prefecture level and only the second stage is reported. Standard errors in parentheses, clustered at the province level. Confucius Value is defined as number of respective number before the Qing dynasty divided by the number of population in the year 1776. The controls include average climate, average war frequency, average slope, latitude and longitude of the prefecture. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

5.3.2 Post-Daoguang Emperor

Since there is evidence that reporting of grain prices became laxer since the emperor Daoguang who began his reign in 1821 (see Luo, 2012, for example), we construct data quality separately for before and after (and including) Daoguang Emperor, and we call them pre-Daoguang and post-Daoguang periods for convenience. The sample split is motivated by one view among historians that, starting from Daoguang, emperors did not value the grain price report as much as before (Yu, 2014).

It is found that the data quality in post-Daoguang period predicts more persistence in transmission when compared to the pre-Daoquang data. Although post-Daoguang period is closer to modern times, it is not immediate that the transmission has to be stronger. In fact, by looking at the data manipulation in the modern period, modern data correlation is low (see Table A1). So, something that happens in the near term does not guarantee that its effect on a present event is stronger than something that happens in the distant past.

To understand the reason for Table 5 Panel A, we carry out another analysis and investigate data quality in pre- and post-Daoguang period and their relation to cultural values. It is shown in Panel B of Table 5 that post-Daoguang data quality is not as strongly correlated to Confucius values when compared to the pre-Daoguang data. It shows that when the monitoring strength is reduced, the moral principle itself is less likely to be an effective constraint for individuals. This exercise shows that the common shock (reduction in monitoring probability) can generate heterogeneous responses and make people deviate from their cultural values. This deviation will then persist over time.

The two exercises show that culture (or repeated past events) has an influence on people. Culture intensifies the incentives created by increasing benefit (Table 4), making culture and the current event more correlated. On the other hand, as can be seen from Table 5, culture cannot replace monitoring.

6 Conclusion

The principal-agent problem arises from the delegation of authority and the misalignment of incentives. This article identifies cultural norms as powerful determinants of the severity of the principal-agent problem. We detect data manipulation in the Qing dynasty (1644-1912) reveals that such cheating behavior has persisted in modern China, for centuries.

Qing prefectural officials were responsible for collecting and report local grain price data. We use the fact that grain prices are seasonal and grain price data cannot stay constant for a prolonged period as an indicator for Qing data manipulation. Employing the instrumental variable approach, we find that Qing data quality reliably predicts data misreporting and exaggeration in modern China. We show that variations of data quality among prefectures are strongly correlated with the severity of famine during the 1959-1961 period and more recent local GDP growth statistics.

We also identify areas where the persistence was higher: treaty port and coastal areas, affluent places where cheating leads to higher rewards. While we find culture amplifies incentive to cheat, we also argue that culture cannot replace monitoring.

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A Additional Tables and Figures

Table A1: Point-wise Correlation Among Main Variables

	DQ_{MC}	GDP Light	GDP Bunching	Famine Severity
DQ_{MC}	1			
GDP Light	-0.185***	1		
GDP Bunching	-0.072	0.069	1	
Famine Severity	-0.165***	0.080	0.059	1

Table A2: The Impact of Qing Data Quality on Data Manipulation – Major Crop Type

Dependent Variables:	GDP Light		GDP Bunching		Famine Severity		First Principal Component	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: OLS								
DQ_{MC}	-0.227***	-0.229**	-0.098*	-0.094**	-0.193***	-0.223***	-0.309***	-0.334***
	(0.059)	(0.057)	(0.047)	(0.044)	(0.053)	(0.064)	(0.088)	(0.091)
Panel B: IV								
$\widehat{DQ}_{MC}$		-0.355***		-0.095*		-0.150***		-0.427***
		(0.053)		(0.052)		(0.051)		(0.105)
Control	N	Y	N	Y	N	Y	N	Y
N	269	269	270	270	240	240	238	238
R-Squared	0.03	0.06	0.01	0.05	0.03	0.05	0.06	0.09

Notes: All regression run at the prefecture level. Standard errors in parentheses, clustered at the province level. Modern prefecture is mapped to the Qing prefecture boundary. The controls include average climate, average war frequency, average slope, latitude and longitude of the prefecture. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table A3: The Impact of Qing Data Quality on Data Manipulation – 3-Month Threshold

Dependent Variables:	GDP Light		GDP Bunching		Famine Severity		First Principal Component	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: OLS								
DQ_{MC}	-0.391***	-0.405**	-0.175*	-0.161**	-0.262***	-0.328***	-0.406***	-0.544***
	(0.124)	(0.109)	(0.092)	(0.079)	(0.076)	(0.081)	(0.125)	(0.115)
Panel B: IV								
$\widehat{DQ}_{MC}$		-0.591***		-0.163*		-0.262***		-0.612***
		(0.128)		(0.087)		(0.082)		(0.109)
Control	N	Y	N	Y	N	Y	N	Y
N	269	269	270	270	240	240	238	238
R-Squared	0.03	0.06	0.01	0.05	0.03	0.05	0.06	0.09

Notes: All regression run at the prefecture level. Standard errors in parentheses, clustered at the province level. Modern prefecture is mapped to the Qing prefecture boundary. The controls include average climate, average war frequency, average slope, latitude and longitude of the prefecture. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Figure A1: Province-Level Average Grain Price

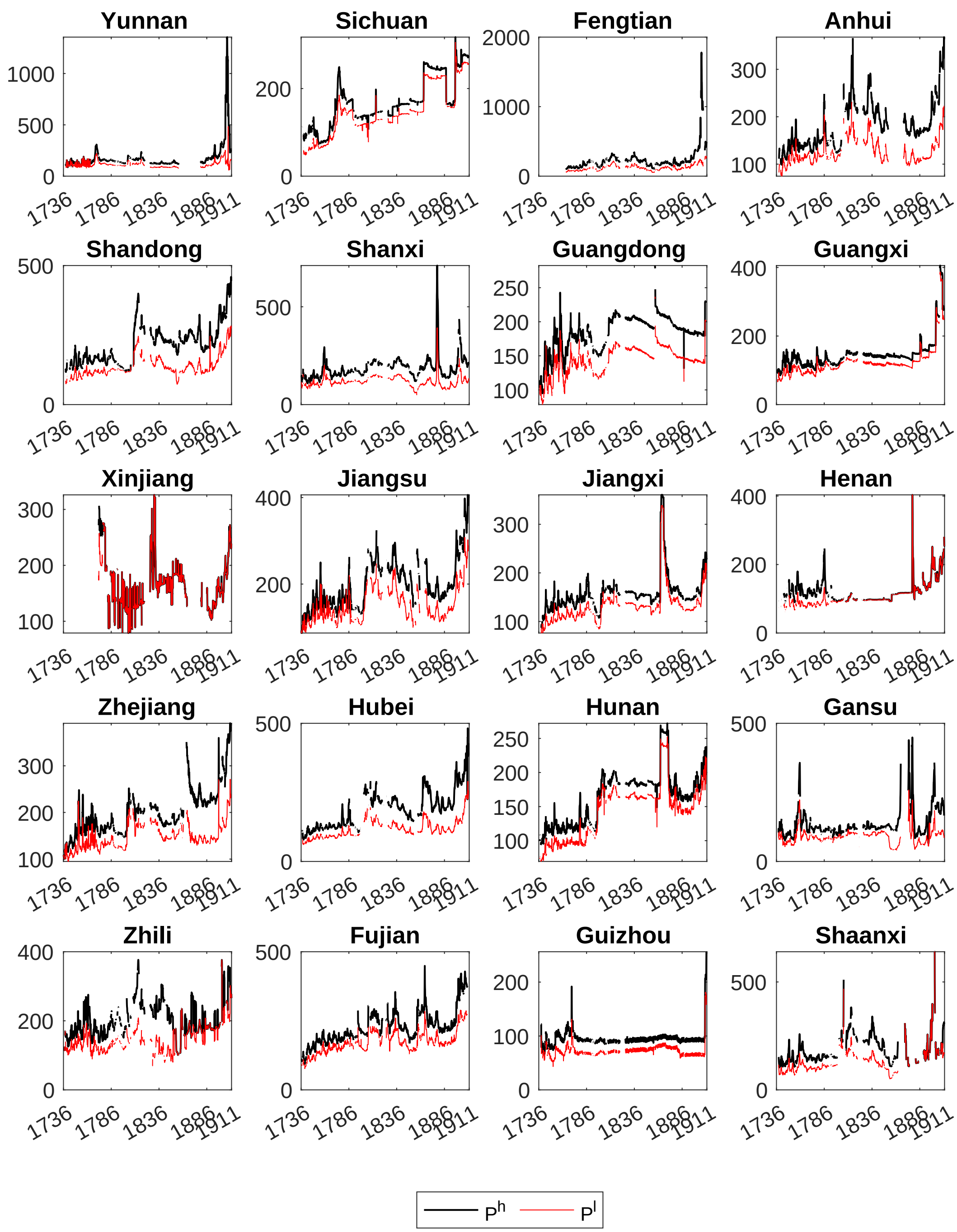
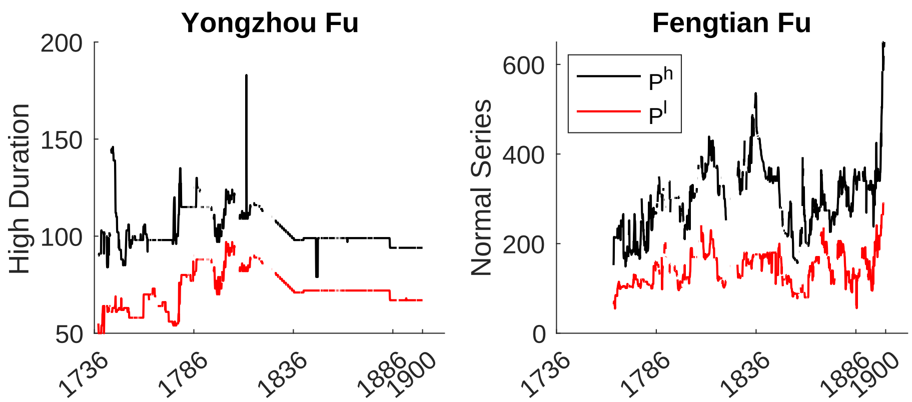
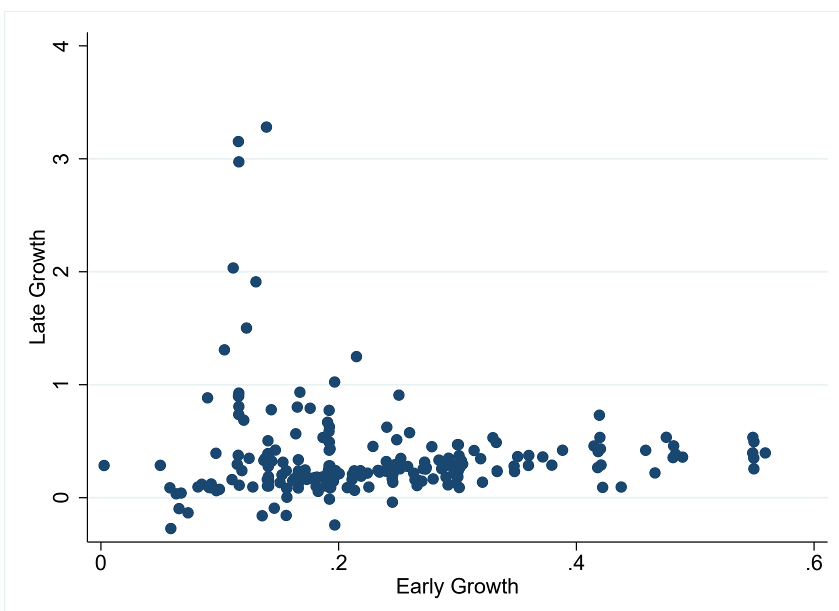


Figure A2: Examples of Wheat Price Data of Different Qualities



Note: For better illustration, observations after 1900 (with extremely high levels) are not plotted. Post 1900, Qing China had hyper-inflation.

Figure A3: The Growth Rate in Prefecture Level



Note: Population Growth in Early and Late Qing Period.