Attention to Inflation*

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Abstract

Macroeconomic models typically predict price dispersion is nondecreasing in inflation, a prediction consistent with pricing patterns observed in recent decades. We show that it does not hold during periods of very high inflation using a new dataset of high-frequency, city-level grain prices from 1940s China. These data demonstrate that price dispersion diminished as inflation soared. We interpret this empirical finding through a pricing model incorporating state-dependent *attention to inflation*, where price dispersion can decrease with inflation at high levels when attention is closer. We offer evidence to support this theory which has important implications for monetary policy in high-inflation environments.

Keywords: Hyperinflation; price dispersion; rational inattention; monetary policy
JEL classification: E31, N15

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> "*One useful insight into how actual inflation may affect expectations about its future path is based in the concept of 'rational inattention.' When inflation is persistently high, households and businesses must pay close attention and incorporate inflation into their economic decisions. When inflation is low and stable, they are freer to focus their attention elsewhere.*"
>
> Jerome H. Powell
>
> Jackson Hole Symposium, August 2022

1 Introduction

In standard New Keynesian models, a key source of the welfare cost of inflation is inefficient price dispersion, which in turn affects the cost of the business cycle, optimal inflation, and the trade-off between inflation and output stability. These workhorse macro models usually indicate that welfare costs rise with inflation. However, most studies on this relationship focus on episodes of relatively low inflation, which have historically been the norm (e.g., Nakamura et al., 2018; Sheremirov, 2020). Our research investigates the relationship between aggregate inflation and price dispersion in high and hyperinflationary environments. This topic is timely, as an increasing number of countries have experienced extremely high inflation rates since the pandemic, and important for developing nations, which often struggle to control inflation and may slip into hyperinflation.

Our analysis proceeds in two parts. First, our theoretical model revisits the predictions of traditional nominal rigidity and information friction models and introduce a parsimonious theory of "state-dependent attention to inflation," motivated by the strong comovement between inflation and attention as measured by newspaper articles covering price-related topics in our sample. This theory also aligns with empirical evidence focusing on recent inflationary episodes (e.g., Pfäuti, 2023; Bracha and Tang, 2024; Weber et al., 2025 etc.). Our analytical results demonstrate that the relationship between inflation and price dispersion can be negative when we account for state-dependent endogenous information acquisition. We also show that the cost of access to information and local economic uncertainty both influence optimal attention to inflation, which, in turn, affects the dispersion of local prices. Second, motivated by these theoretical insights, the empirical part evaluates the relationship between price dispersion and inflation using a unique high-frequency, city-level dataset covering the entire hyperinflation era in the 1940s in China. We find a robust, negative relationship between cross-city price dispersion and nationwide inflation. Additional empirical tests

suggest that the information friction channel—consistent with the state-dependent attention to inflation highlighted in the theory—could explain this pattern. This distinguishes our findings from existing studies focusing on relatively low inflation scenarios.

Our theory adopts a standard incomplete information setting that features a signal extraction problem à la Lucas (1973), and endogenous information acquisition following Sims (2003), with a specific emphasis on pricing. In this model, the representative firm on each island faces a costly information problem of choosing a precision that maximizes expected profits minus the cognitive costs of making more precise decisions relative to the ex-post optimum. The key departure from the traditional rational inattention model is a profit (loss) function that depends on the aggregate state, motivated by the recent empirical evidence on state-dependent attention.

An analytical solution of this model shows that attention depends on the cost of information, prior uncertainty, and aggregate and idiosyncratic states, which are standard in this class of models. Moreover, attention can be a key driver of price dispersion. First, incomplete information leads to individual underreaction, the extent of which affects price dispersion from idiosyncratic factors such as local productivity shocks. Second, noisy signals translate into dispersed prices even without firm heterogeneity, with price dispersion determined by the endogenously chosen signal precision. While an analytical expression is not always achievable, we show that in the second channel, price dispersion can decrease with attention as long as the optimal signal is sufficiently precise. Altogether, our theory provides a new perspective on the relationship between inflation and price dispersion through the attention channel.

More importantly, these results provide useful insights for empirically testing the relationship between inflation and price dispersion. First, we can express the local price as a function of past prices, linked via a function of aggregate and idiosyncratic states that capture state-dependent attention. Second, local features such as the ease of access to information and local productivity can matter for attention, which affects the primary relationship we study. Thus, controlling for these factors is crucial in the empirical exercise.

Our empirical analysis relies on a hand-collected historical dataset of city-level grain prices from the hyperinflation period of the 1940s in China, merged with data on wars and city-level characteristics related to goods trade. The detailed, high-frequency price data enable us to study price-setting behaviors and uncover underlying mechanisms during hyperinflation. Our findings show that city-level prices converge faster toward the national mean as inflation rises. Consequently, price dispersion decreases when aggregate inflation increases in a very high-inflation environment.

This result remains robust when we control for (potential) confounding factors such as wars disrupting cross-region information or goods flow and city-specific characteristics like trade access and suitability for rice or wheat. A battery of robustness tests, including subsample analysis, alternative specifications and GMM estimation, lend additional support for this finding.

This result contrasts with standard macro models, which typically imply a positive relationship between inflation and price dispersion (e.g., Nakamura et al., 2018; Alvarez et al., 2019). Our theory, which highlights the often-overlooked role of inattention to macro events, provides a potential explanation for this new finding. Based on our theory, acquiring noisy information about the aggregate economy, particularly aggregate prices, is costly for individual firms, especially during our sample period when access to information could entail significant costs. When inflation is low, firms pay little attention to the aggregate price level, as the cost of misoptimization is inconsequential. However, during high inflation or hyperinflation episodes, this cost becomes enormous. Consequently, firms closely monitor price signals and effectively align better with aggregate inflation, which reflects the market average of individual prices.

We provide further empirical evidence supporting our attention theory. First, we compare our results with those from a low-inflation period using the same econometric approach and find that the relationship between price dispersion and inflation is positive, consistent with existing studies of low-inflation times. This suggests that inflation levels indeed play an important role. Second, we divide cities in our sample into two groups: those near large cities and those farther away. The distance from large cities determines the ease of accessing information, i.e., the information cost. Consistent with our theory, the impact of rising inflation on price convergence is more pronounced for cities closer to large cities. In other words, price dispersion is lower among cities closer to large cities than those farther away, conditional on aggregate inflation. This observation further supports the role of information frictions in interpreting our findings. Third, we gathered newspaper data on price-related coverage as a proxy for public attention to inflation. This includes occurrences of keywords such as "price," "inflation," "living costs," and other similar terms in the article titles, following a similar approach to recent literature such as Song and Stern (2023) and Flynn and Sastry (2022). Our text-based attention measure strongly correlates with inflation, regardless of the newspaper or the measurement of "attention." While mostly suggestive, this finding further supports the state-dependent attention explanation emphasized in our theory.

Taken together, we highlight the role of state-dependent attention in understanding the classic relationship between price dispersion and inflation within a theoretical framework and provide

empirical evidence from a high-inflation environment that supports our model's prediction and mechanism. We believe that the state-dependent attention to inflation has important implications for the welfare cost of inflation and the efficacy of monetary policy as inflation becomes very high.

We make three primary contributions to the literature. First, we create a novel and comprehensive city-level price dataset which other scholars can utilize to explore various intriguing questions in macroeconomics and economic history. Second, we identify a markedly different empirical relationship between aggregate inflation and price dispersion during periods of very high inflation, which poses a potential challenge to standard New Keynesian macro models and their positive and normative implications for monetary policy. Third, we present a parsimonious theory that illustrates the underlying factors determining state-dependent attention allocation. Our theoretical result not only guides the empirical exercise but also provides new insights into the effectiveness of monetary policies under different inflation regimes through the endogenous and state-dependent attention channel.

Our paper relates to several large literature in macroeconomics. The first examines the empirics of price-setting and price dispersion. Reinsdorf (1994) finds that price dispersion rose when inflation fell using BLS microdata. Nakamura et al. (2018) find no significant change in price dispersion as inflation increased during the Great Inflation era in the U.S., arguing that menu cost model predictions better align with these results than the Calvo model. Sheremirov (2020) reports that price dispersion increases with inflation during the low-inflation period of 2002-2012. Using scanner data on retail product prices, Sara-Zaror (2021) documents that the price dispersion for identical goods increases steeply around zero inflation and flattens as inflation rises. More recently, Cavallo, Lippi and Miyahara (2023) estimate price dispersion and the welfare cost of inflation using granular price data. All of these essays examine low-inflation environments. We are one of the first essays to examine detailed data on price setting in a nation experiencing hyperinflation.

The second includes several studies that have examined price dispersion during high-inflation episodes in Latin America. Alvarez et al. (2019) and Gagnon (2009) study high-inflation episodes in Argentina and Mexico, respectively. Both employ a menu-cost model framework. Rather than relying on quantitative models, our work takes an agnostic approach by providing reduced-form results on this relationship using a richer dataset. In Section 2.1, we also review standard monetary models, including the Calvo pricing model, menu-cost model, and exogenous information friction models. We show these standard models cannot predict a concave relationship between inflation and price dispersion, where the relationship is positive at low levels and negative at high levels of

inflation.

The third is the literature on rational inattention in macroeconomics (e.g., Sims, 2003; Reis, 2006; Maćkowiak and Wiederholt, 2009; Alvarez, Lippi and Paciello, 2016), the insights of which our model builds upon. More specifically, our model belongs to a class of models featuring *state-dependent* attention. The assumption of a general loss function is motivated by observations in recent empirical studies (e.g., Cavallo, Cruces and Perez-Truglia, 2017; Weber et al., 2025; Bracha and Tang, 2024) that aggregate price and inflation "levels" matter for the attention, as opposed to the primary focus on "volatility" or "uncertainty" in most existing frameworks, such as those by Stevens (2020), Turen (2023), Mikosch et al. (2024) and Pfäuti (2024), among others. In this regard, our framework is particularly related to Flynn and Sastry (2022), Flynn and Sastry (2023), and Chiang (2022), which model attention as being dependent on the underlying state of the economy. Moreover, our focus on the role of attention in understanding price setting and dynamics follows in the footsteps of Woodford (2009), Maćkowiak and Wiederholt (2009), Paciello and Wiederholt (2014) and Matějka (2016), among others (see Maćkowiak, Matějka and Wiederholt, 2023 for a comprehensive summary). While our model shares key features with these studies, such as costly and endogenous information acquisition, our theoretical framework emphasizes "attention to inflation" and its implications for price dispersion.

The rest of this paper proceeds as follows. Section 2 presents a model of attention to inflation and compares it with standard pricing models. Section 3 introduces our novel historical dataset within its historical background. Section 4 discusses our empirical strategy and presents the estimation results. Section 5 concludes the paper.

2 A Model of Attention to Inflation

In this section, we present the predictions of existing models alongside a new framework that features attention to inflation to clarify the relationship between price dispersion and inflation. China's domestic grain market in the 19th and early 20th centuries was characterized by a high degree of integration, driven by trade liberalization and reduced transportation costs. For instance, the establishment of treaty ports in the 1800s not only spurred the development of port markets but also facilitated their integration with neighboring regions. This phenomenon of integrated yet geographically dispersed markets can be modeled within a New Keynesian framework, where the representative firm in each city participates in a monopolistically competitive, nationwide grain

market.

2.1 Overview of Traditional Models

Traditional time-dependent and state-dependent models have clear predictions of the relationship between price dispersion and inflation. In Calvo models, where a fraction α of prices remains unchanged each period, dispersion of log prices $\Delta_t \equiv var_i[\log p_t(i)]$ can be solved in closed form (see, Woodford, 2003 chap. 6): $\Delta_t = \alpha\Delta_{t-1} + \frac{\alpha}{1-\alpha}\pi_t^2 + h.o.t$. The intuition behind this result is that as prices are sticky, past price dispersion matters for today's. When firms do adjust prices, they adjust more if the overall rate of inflation is higher. As only a fraction of firms can adjust, the cross-sectional dispersion of prices, in turn, becomes higher.

Menu cost models (e.g., Golosov and Lucas Jr., 2007; Alvarez et al., 2019; Nakamura et al., 2018) predict a more complicated relationship between price dispersion and inflation that depends on the "state," i.e., aggregate inflation. When inflation is low, the dispersion of prices is insensitive to inflation because it mainly reflects idiosyncratic shocks. When inflation becomes very high, prices are adjusted more frequently, but the inaction sS range becomes wider as inflation rises, leading to a higher dispersion of prices.[1]

Information friction models, particularly those featuring exogenous information such as noisy signals (e.g., Drenik and Perez, 2020; Hellwig and Venkateswaran, 2009), can also generate price dispersion. However, they do not typically predict a relationship between price dispersion and aggregate inflation, as dispersion is mainly driven by the volatility of the aggregate state and precision of the price signals.

Taken together, under a high-inflation environment, traditional pricing models predict that price dispersion is non-decreasing with inflation. In the next subsection, we provide a parsimonious theory of pricing with endogenous information acquisition and show that the prediction can be different. In Section 4, we provide empirical evidence on the relevance of this model in our high-inflationary context.

2.2 Price Dispersion under Attention to Inflation

We build on the island model in Lucas (1973), but allow for endogenous information acquisition and state-dependent attention. A representative firm in each city has limited capacity to understand

[1] Alvarez et al. (2019) prove that the elasticity of unconditional price dispersion with respect to inflation has an upper bound of one third for large enough inflation. And this result doesn't depend on the size of the volatility of idiosyncratic shocks as long as inflation is large enough.

the aggregate state of the economy; instead, they must pay information costs to obtain more precise signals and make more precise optimization decisions. Our objective is to theoretically demonstrate how the cost of misoptimization can endogenously fluctuate with the aggregate state, and to explore its implications for firms' attention allocation and the resulting price dispersion.

Information and Price Setting. Denote the payoff-relevant state for an individual firm i by $\Theta_{it} = (\theta_{it}, \theta_t)$, where θ_{it} and θ_t summarize the idiosyncratic and aggregate states respectively, and θ_t is usually endogenously pinned down in equilibrium. With imperfect information on the underlying state of the economy Θ_{it}, firms learn the optimal price p^*_{it} from a noisy Gaussian signal s_{it}. Moreover, they choose the precision of this signal, subject to a cost that is proportional to the Shannon mutual information. Specifically, the prior distribution of p^*_{it} and the signal s_{it} take the form

$$p^*_{it} \sim N(\bar{p}_{it}, \sigma_i^2) \tag{2.1}$$

$$s_{it} = p^*_{it} + \frac{\epsilon_{it}}{\tau_{it}},\ \epsilon_{it} \sim N(0,1) \tag{2.2}$$

where τ_{it} denotes the endogenous precision of signal s_{it}, which we call "attention." $\bar{p}_{it}$ and σ_i^2 are the mean and variance of the prior distribution of optimal price p^*_{it}. As a result, the firm sets a price based on the posterior distribution of p^*_{it}, that is, $\hat{p}_{it} = \mathbb{E}(p^*_{it}|s_{it})$. Specifically,

$$\hat{p}_{it} = \mathbb{E}(p^*_{it}|s_{it}) = \frac{\sigma_i^2}{\sigma_i^2 + \frac{1}{\tau_{it}^2}} \left(p^*_{it} + \frac{\epsilon_{it}}{\tau_{it}} \right) + \left(1 - \frac{\sigma_i^2}{\sigma_i^2 + \frac{1}{\tau_{it}^2}} \right) \bar{p}_{it} \tag{2.3}$$

The Attention Problem. We now characterize and solve the firm's optimization problem. Assume that the cost associated with the Shannon mutual information is

$$\lambda_i \mathcal{I}(s_{it}; p^*_{it}) = \frac{1}{2} \lambda_i \log \left(\frac{\sigma_i^2}{\sigma^2_{p^*_{it}|s_{it}}} \right) = \frac{1}{2} \lambda_i \log \left(1 + \tau_{it}^2 \sigma_i^2 \right) \tag{2.4}$$

The cost function combines the change in entropy of the random variable p^*_i, given by $\mathcal{I}(s_i; p^*_i)$, of which the variance reduces from $\sigma^2_{p^*_i}$ to $\sigma^2_{p^*_i|s_i}$ due to the additional information embedded in signal s_i, and a scaling factor λ_i, which captures the individual cost of access to information. As can be easily seen, a more precise signal, shown as a larger τ_i, is more costly to acquire.

The firm's problem is to choose the signal precision to maximize its expected real profit net of

the information cost, formalized as the following static problem:

$$\max_{\tau_{it}} \mathbb{E}_{p^*_{it}} \left[\mathbb{E}_{s_{it}} \left[\vartheta(\Theta_{it}) \left(p^*_{it} - \mathbb{E}(p^*_{it}|s_{it}) \right)^2 \right] \right] - \frac{1}{2} \lambda_i \log \left(1 + \tau^2_{it} \sigma^2_i \right) \tag{2.5}$$

where $\vartheta(\Theta_{it})$ captures the cost of misoptimization that depends on both idiosyncratic and aggregate states. Solve for the optimization problem (2.5), we can derive an analytical formula for the optimal attention level τ^*_{it} that depends on the cost of information λ_i, the prior variance of the optimal price σ^2_i, and the state Θ_{it}

$$\tau^*_{it} = \sqrt{\frac{\vartheta(\Theta_{it})}{\lambda_i} - \frac{1}{\sigma^2_i}} \tag{2.6}$$

This is a similar expression as in Maćkowiak, Matějka and Wiederholt (2023) and Bracha and Tang (2024) that highlights the three key drivers of attention. Attention tends to rise when the underlying state is more uncertain or when access to information is less costly. More importantly, attention can depend on the underlying state Θ_{it}, motivated by the recent empirical evidence on time-varying state-dependent attention, including the specific focus on attention to inflation.[2] Theoretically, this state-dependence represented by $\vartheta(\Theta_{it})$ can, for instance, come from sources such as the state-dependent profit-curvature and risk-price channels highlighted in Flynn and Sastry (2022) and contingency planning as in Maćkowiak and Wiederholt (2018). In this paper, however, we do not take a strong theoretical perspective on the underlying source of this state-dependence but focus on the implication of "attention to inflation" for state-dependent price dispersion.[3]

Price Dispersion. Let us start with the case with homogeneous firms, i.e., when $(\lambda_i, \sigma_i, \Theta_{it}, \bar{p}_{it})$ are homogeneous across firms. In this scenario, individual attention is also homogeneous, say, at τ^*; therefore, cross-sectional price dispersion is: $\sigma_{\hat{p}_i} = \tau^*/(\tau^{*2} + \frac{1}{\sigma^2_i})$, which is solely driven by the optimal attention τ^* given prior uncertainty about the optimal price σ_i. Moreover, if $\tau^* > 1/\sigma_i$, $\sigma_{\hat{p}_i}$ decreases with τ^*, i.e., price dispersion decreases with the optimal attention level. This result, combined with supporting empirical evidence that attention to inflation tends to rise with inflation, implies that under certain parameterization, price dispersion can decrease as inflation rises.

In the case of heterogeneous firms, not only does aggregate state affect price dispersion, but also

[2] Recent works by Flynn and Sastry (2022) and Flynn and Sastry (2023) provide a "strategic mistakes" framework that endogenizes the attention problem. Flynn and Sastry (2023) make a theoretical prediction of the relationship between price dispersion and inflation that is inconsistent with our empirical finding.

[3] An illustrative state-dependent attention model is presented in Appendix A, where optimal attention varies with the optimal profit. Intuitively, the costs of making pricing mistakes depend on the size of the economy; when the size is big, stakes of accurate pricing are high, which leads to more attention to the underlying states.

cross-firm differences such as heterogeneous priors, idiosyncratic shocks, and heterogeneous access to information. Appendix A provides an illustrative model with an explicit formula for such a case. It is, therefore, crucial to control for these idiosyncratic factors in the empirical analysis.

2.3 Bridging Model and Empirics

The endogenous attention theory delivers two key results that are relevant to our understanding of the relationship between inflation and price dispersion. First, individual attention varies with idiosyncratic state θ_{it}, aggregate state θ_t, and information cost λ_i. Second, price dispersion varies with the attention level.

Consider a prior that is determined by the entire past realization of prices $(\hat{\mathbf{p}}_{i,t-1}, \hat{\mathbf{p}}_{t-1}) = (\hat{p}_{i,t-1}, \hat{p}_{i,t-2}, ..., p_{t-1}, p_{t-2}, ...)$, Equation (2.3) can be rewritten as

$$\hat{p}_{it} = \omega_1(\Theta_{it}|\lambda_i, \sigma_i)\hat{\mathbf{p}}_{i,t-1} + \omega_2(\Theta_{it}|\lambda_i, \sigma_i)\hat{\mathbf{p}}_{t-1} + \omega_3(\Theta_{it}|\lambda_i, \sigma_i)p^*_{it} + \varsigma_{it} \tag{2.7}$$

$\hat{p}_{it}$, the random pricing of firm i, is a combination of past idiosyncratic prices, aggregate prices, and a signal for optimal price with endogenous precision. The weight on each term is a function of the aggregate state at given idiosyncratic parameters (λ_i, σ_i) due to the state-dependent endogenous attention. Empirically, given our focus on inflation as an aggregate state, we can estimate a panel regression of regional prices on its lags while allowing for inflation-dependent coefficients and controlling for regional factors as well as time and regional-level fixed effects, which we turn to next.

3 Background and Data

Conventional studies of price setting primarily focus on low-inflation episodes partly because hyperinflation is rare and typically short-lived. Moreover, micro-level price data in such events are often difficult to obtain. In our empirical setting, inflation remained persistently high throughout our sample period. Local government officials kept a close record of local price data at a high frequency (at least every two days). In addition, government regulation of prices was temporary and ineffective. These historical backgrounds provide a unique and valuable opportunity to study price adjustments in a persistently-high-inflation environment. In this section, we discuss in detail our dataset against this unique historical background.

3.1 Background: Hyperinflation in the 1940s

In the 1940s, China was engulfed in two major wars: the Second Sino-Japanese War (1937-1945, part of World War II) and the Chinese Civil War (1946-1949, hereafter referred to as the Civil War). This period also saw an unprecedented hyperinflation crisis. We provide a brief overview of the development of hyperinflation during these wars as well as the government's policy responses.

Hyperinflation began in 1939 as Japanese forces gradually occupied eastern territories of China, triggering mass migration to the western provinces such as Yunnan, Guizhou, and Sichuan. As a result, population increased in these regions along with a rise in wages driven by significant infrastructure spending. These changes led to higher grain and cotton yarn prices, which then spread to other goods. The increased cost of living caused nominal wages to further rise, creating a wage-price spiral (Chang, 1958). A sharp decline in government revenues, wartime supply shortages, and excessive money creation by the central bank further exacerbated the rising general price levels.

China's victory in World War II in August 1945 sparked optimism about postwar economic recovery. In the following months, grain prices dropped significantly for the first time in years. However, the outbreak of the Civil War caused prices to surge again. Hyperinflation worsened as unchecked military expenditures were financed through money issuance. According to the Central Bank statistics, the general price level in Chungking City, the wartime capital from September 1940 to May 1946, skyrocketed by over 30 million times between January 1946 and April 1949.

Throughout the 1940s, the government attempted to monitor and control hyperinflation, but these efforts were largely ineffective. In May 1941, recognizing the importance of food during wartime, the government established the Ministry of Food to gather grain market information daily or every other day and to procure food for military needs. The government also intervened in economic activities by freezing prices and wages during both wars. However, these price controls were implemented only in a few major cities, referred to as "special municipalities," such as Nanking, Shanghai, and Chungking. These measures were short-lived due to ineffective governance (see Chang, 1958). Further details on these price regulation policies and their failures are provided in Appendix B.2.

On August 19, 1948, the Nationalist government swiftly enacted a currency reform to prevent further economic collapse. A new currency, the *Gold Yuan Certificate*, replaced the old currency, *Fabi*, at a rate of one to three million. Unfortunately, this reform also quickly failed, effectively serving as a mere currency exchange and causing prices to rise even faster. The monetary system

eventually collapsed, and the government went bankrupt in credit in early 1949.

3.2 Data Construction

We manually collect and digitize thousands of historical files, which form three primary datasets: city-level grain prices, battlefields, and newspaper coverage of prices. Below, we briefly describe these datasets and direct readers to Appendix C for further details.

City-Level Prices. Our city-level price dataset consists of wholesale grain prices from 314 cities across 28 provinces in China, covering the years 1941 to 1948. We manually digitize the grain price data from three internal periodicals published by the Ministry of Food. These price data were collected by local government officials—who reported to the Ministry via telegraph—and reflect the average grain price of wholesale markets in each city.

Due to limited governing capacity in certain regions, the Ministry was unable consistently collect grain price data for all 314 cities in every period. Additionally, our sample does not include data for areas not controlled by the Nationalist government, specifically cities under Communist Party control and those occupied by Japan. Data availability fluctuated over time as state capacity and war situations evolved. The first periodical, the *Grain Briefs*, reports daily rice prices from April 1, 1941, and daily wheat prices from April 30, 1941, to December 25, 1942. Initially, it only covered Chungking City and cities in Sichuan province but gradually expanded to all cities controlled by the Nationalist government around April 1942. The second periodical, the *Grain Weekly Report*, covers daily grain prices from December 19, 1942 to June 30, 1944; whereas the third source, the *Grain Ten-Day Report*, records prices every two days from July 2, 1944, to November 30, 1948. More details on our data source are provided in Appendix C.1.

All prices were denominated in fabi yuan for every 50 kilograms[4] of grain before the currency reform on August 19, 1948, after which the currency was switched to Gold Yuan. We convert all post-reform prices back to fabi using an exchange rate of 1 Gold Yuan to 3,000,000 fabi yuan. The raw data are then seasonally adjusted to eliminate price fluctuations caused by seasonal factors. In our empirical exercise, we calculate weekly averages of grain prices to standardize data frequencies across different periods and to smooth out intra-week price fluctuations within each city. To mitigate the potential impact of an unbalanced panel, we analyze subsamples covering various time periods. In a robustness test, we also exclude cities with many missing observations from our analysis.

[4]In the original archives, the unit was *shidan* (in Chinese, 市石/市担)=100 *shijin* (in Chinese, 市斤) equivalent to 50 kg.

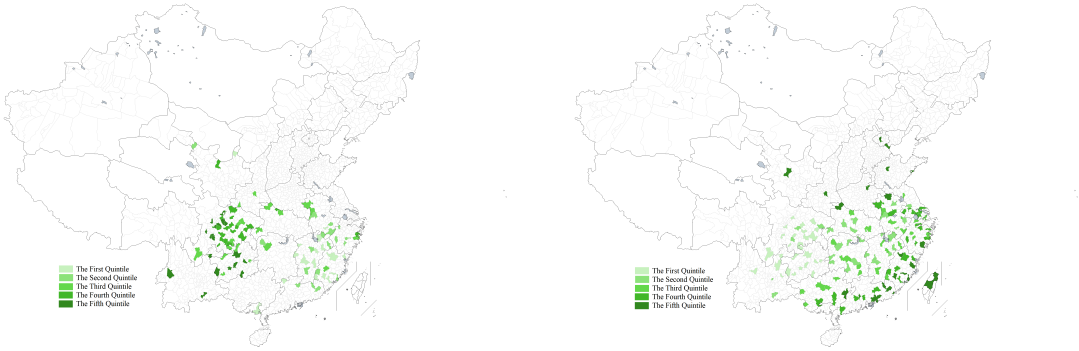
Figure 1 illustrates the geographical distribution of prices using snapshots of raw data from November 1944 and November 1946. Several observations emerge from these snapshots. First, our sample includes fewer cities before the end of WWII in 1945 due to the inaccessibility of data from Japanese-occupied regions. Second, our rice data predominantly come from southern regions, while wheat data mostly originate from the north, reflecting regional dietary preferences—southern China mainly consumes rice, whereas northern China favors wheat-based foods. Third, there are substantial price variations across regions, as shown in both panels. The primary focus of this paper is to study how this geographical distribution of prices evolves over time as inflation changes.

To validate our use of grain prices as proxies for the general price level in each city, we collect daily wholesale price indices from the Central Bank's internal periodical, the *Financial Weekly*. These data cover the period from November 1945 to April 1949 but are limited to four major cities: Shanghai, Chungking, Canton, and Kunming. In the 1940s, as an underdeveloped country, China relied heavily on agricultural output, constituting a significant portion of its GDP. The wholesale price index is based on the weighted average prices of 23 categories of goods, with rice and wheat prices assigned weights of 38.6% and 13.7%. Therefore, although a comprehensive price index for all cities is unavailable, the rice and wheat prices used in our study should effectively represent the general price level well. Figure 2 depicts the year-over-year changes in rice, wheat, and wholesale prices for Shanghai and Chungking, where general price indices are available. As conjectured, given their significant weight in its construction, the trends in rice and wheat prices closely mirror those of the wholesale price index. Moreover, annual inflation rates remained remarkably high throughout our sample period and showed a continued rising trend.

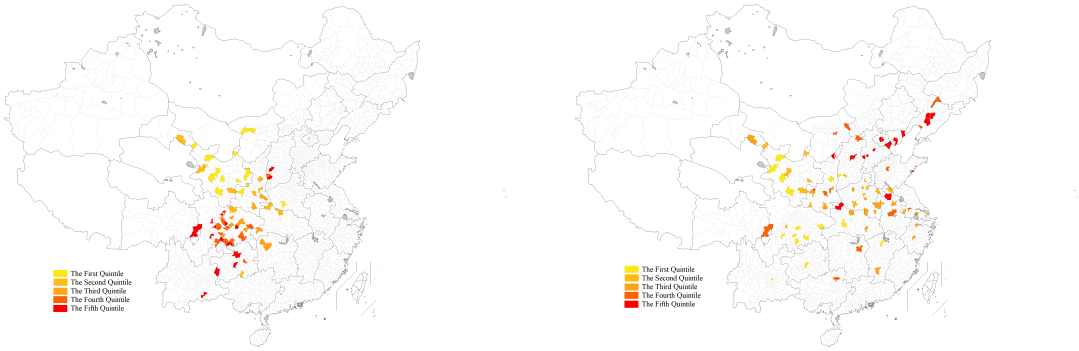
Nationwide Prices. Since a nationwide high-frequency aggregate price index for the 1940s is unavailable, we construct one using our city-level grain price data. Specifically, we calculate both a simple average and a population-weighted average of grain prices across cities. The nationwide inflation rate is then derived from the log change in this index. The population-weighted average price change, which serves as our baseline aggregate inflation rate, is shown in Figure 3. We make three observations from this plot. First, rice and wheat price inflation rates are nearly identical throughout the period under study. Second, inflation remains high for most of the sample, except for a brief decline from the end of WWII in 1945 to the end of 1946, when year-over-year inflation fell below 0. Third, there's significant time-series variation in inflation rates: during the first half of the sample, inflation fluctuated between 0% and 200%, while in the second half, it steadily rose to

Figure 1: Geographical Distribution of Rice and Wheat Prices

(a) Distribution of Rice Prices

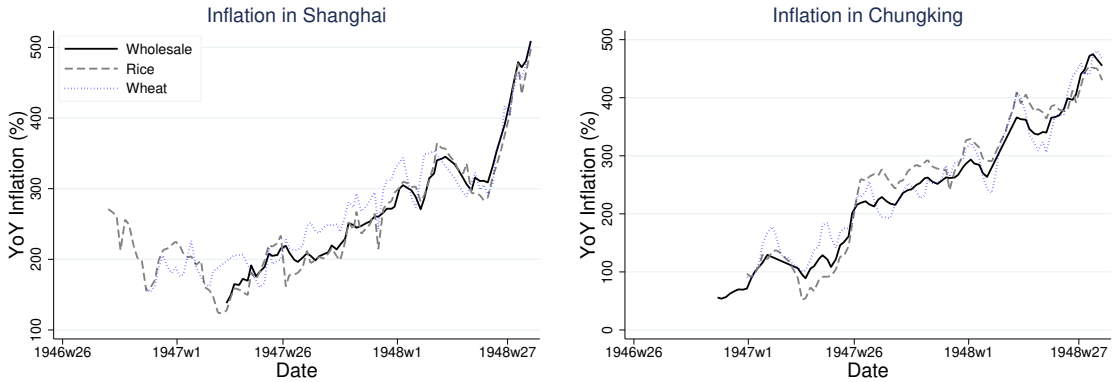


(b) Distribution of Wheat Prices



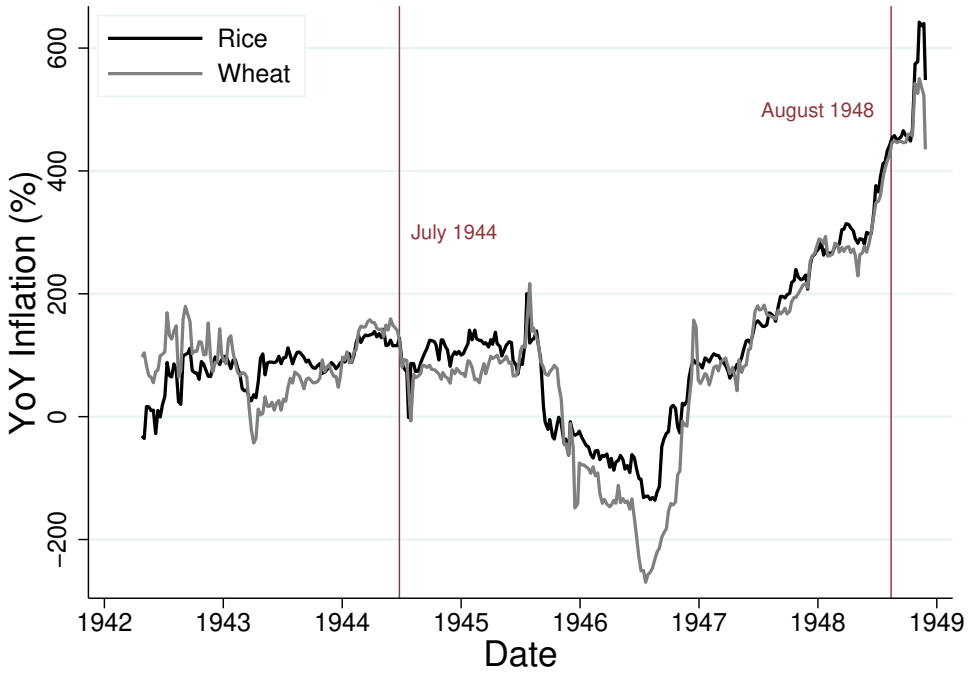
Notes: This figure presents the geographical distribution of rice and wheat prices by quintiles for November 1944 (left) and November 1946 (right), two representative samples from the WWII and Civil War periods. Source: The *Grain Ten-Day Report*.

Figure 2: City-Level Inflation



Notes: These figures present the weekly year-over-year inflation rates from the end of 1946 to August 1949, using wholesale price indices (solid black lines), rice prices (black dashed lines), and wheat prices (blue dotted lines) for Shanghai (left) and Chungking (right). Source: The *Grain Ten-Day Report* and the *Financial Weekly*.

Figure 3: Aggregate Inflation



Notes: This figure presents the weekly year-over-year nationwide inflation rates measured using rice or wheat price data. Aggregate prices are calculated as the population-weighted averages of city-level prices.

over 400%. The August 1948 currency reform did not alleviate this trend but instead accelerated it. These observations make this historical episode particularly relevant for empirically studying pricing behaviors during periods of high inflation.

Battlefields. Throughout our sample period, there were thousands of combats or conflicts, and we primarily focus on major battles due to their stronger impact on the market and information frictions we are investigating. We compile a dataset with spatiotemporal information on 145 major battles during the two wars of the 1940s, spanning from April 1941 to November 1948. For each battle, we document its duration (start and end dates) and the location of its primary battleground. Using this information, we construct a war exposure indicator, $war_{i,t}$, for each city i at each time t. Specifically, $war_{i,t} = 1$ if there was a major battle within k kilometers of city i at time t. In our baseline analysis, we set $k = 50$ kilometers; our results are not sensitive to alternative measures. It's worth noting that in some major military actions directly targeting specific cities, grain prices for those cities were unavailable. In such cases, our empirical analysis effectively examines pricing behavior in cities exposed to nearby wars.

Newspaper Coverage of Inflation. We analyze articles from three prominent newspapers of the time, *Shun Pao*, *Sin Wan Pao*, and *Ta Kung Pao* (申报, 新闻报, and 大公报, in Chinese), to examine how public attention to inflation shifted over time. These newspapers were published daily during the 1940s. To construct a measure of public interest in inflation, we count articles that contain keywords such as "general price levels (物价)," "prices (价格)," "grain prices (粮价)," "rice prices (米价)," "price indices (物价/价格指数)," "inflation (通货膨胀)," and "cost of living indices (生活费指数)" in their headlines. Expanding the search to article charts and main texts gives similar results.

3.3 Descriptive Statistics

Table 1 presents inflation statistics based on grain prices. Using weekly grain prices for each city, we calculated week-over-week and year-over-year inflation rates. Similar statistics were derived for rice and wheat inflation. On average, city price levels rose by 3%-4% per week or approximately 180% annually. We then computed population-weighted average grain prices across cities to generate a nationwide inflation series. Aggregate price levels increased at a weekly rate of 2.6% or a yearly rate of around 100% annually, from 1941 to 1948, which is comparable in magnitude to city-level average inflation.

Table 1: Summary Statistics

	Mean	Median	Max	Min	S.D.	# of Obs.
A. City-Level Inflation (%)						
Weekly Rice Price Change	3.7	1.1	356.0	-349.4	25.6	42,885
Weekly Wheat Price Change	3.3	0.7	628.5	-415.8	28.8	25,110
Yearly Rice Price Change	179.8	146.6	842.3	-199.6	143.3	28,435
Yearly Wheat Price Change	177.7	146.8	786.6	-143.5	134.5	14,976
B. Nationwide Inflation (%)						
Weekly Rice Price Change	2.6	2.1	124.9	-86.2	18.5	400
Weekly Wheat Price Change	2.6	1.5	120.2	-92.4	20.7	394
Yearly Rice Price Change	112.5	93.9	642.3	-136.1	136.5	349
Yearly Wheat Price Change	96.8	84.0	550.4	-269.5	149.1	343
C. Cross-City Price Dispersion						
Dispersion of Rice Price	1.5	1.4	2.4	0.5	0.4	401
Dispersion of Wheat Price	1.6	1.6	3.7	0.5	0.5	396

Notes: This table presents statistics of inflation calculated from city-level rice or wheat price data in the entire sample. City-level inflation is calculated as each city's week-over-week or year-over-year grain price changes. Nationwide inflation is calculated as week-over-week or year-over-year changes in nationwide grain price, which is the population-weighted average prices across cities. Price dispersion is calculated as the cross-city standard deviation of log rice or wheat weekly average prices.

4 Empirical Results

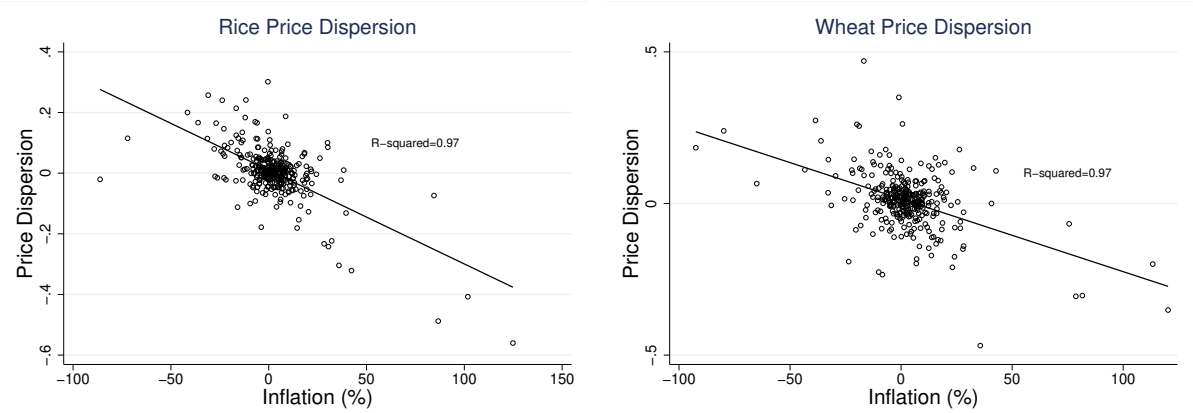
We investigate the empirical relationship between price dispersion and inflation from two perspectives. First, we examine the time-series relationship between nationwide price dispersion and inflation. Second, we leverage the rich information in our panel data to focus on the convergence of prices across cities, providing indirect evidence of how inflation influences price dispersion.

4.1 Time Series Evidence

To begin, we present time-series evidence on the relationship between cross-city price dispersion and nationwide inflation in our high-inflation context. Motivated by the classical relationship between price dispersion and inflation, we account for the persistence of price dispersion by employing a simple OLS regression model: $\sigma_t = \text{constant} + \beta_\sigma \sigma_{t-1} + \beta \pi_t + \eta_t$, applied to each grain price series, where σ_t represents the standard deviation of log prices across cities and π_t denotes the population-weighted nationwide average inflation.

Figure 4 plots $\sigma_t - \beta_\sigma \sigma_{t-1}$ against π_t, with the slope representing the OLS estimate of β. While weekly inflation often hovers around zero, notable price fluctuations can occur, with aggregate

Figure 4: Cross-City Price Dispersion v.s. Aggregate Inflation



Notes: The figures present the nationwide week-over-week log price changes of rice (left) and wheat (right) against the dispersion of these prices across cities, conditional on the lagged one-week price dispersion. To achieve this, we first fit a simple OLS regression $\sigma_t = \text{constant} + \beta_\sigma \sigma_{t-1} + \beta \pi_t + \eta_t$ for each grain price series and then plot $\sigma_t - \hat{\beta}_\sigma \times \sigma_{t-1}$ against π_t. The sample period spans from April 1942 to August 1948.

prices doubling in some weeks. Leveraging this temporal variation in inflation, we observe a strong negative correlation between price dispersion and inflation—higher inflation is associated with significantly reduced price dispersion. Moreover, the high R-squared value of this simple regression suggests that inflation and past dispersion can explain nearly all the variation in current dispersion.

Despite the simplicity of this model, the finding contrasts starkly with theoretical predictions from classical models, as discussed in Section 2, and with empirical evidence from periods of relatively low inflation (e.g., Nakamura et al., 2018; Sheremirov, 2020). This suggests that a different channel may become relevant when inflation transitions from moderate to very high levels, a topic we further explore in Section 4.4.

4.2 Cross-City Evidence

Figure 4 illustrates a straightforward relationship between price dispersion and inflation. However, aggregating micro-level prices to calculate the standard deviation overlooks a wealth of detailed information that could significantly influence price dynamics, such as wartime conditions that increase trade and information frictions across cities. As noted in Section 3.1, wars occurred throughout our sample period with considerable geographical variation, making it challenging to construct an aggregate measure of war to better discern its impact alongside inflation.

To fully utilize the micro-level features of our data, we investigate how price convergence varies with inflation as an indirect test of the relationship between price dispersion and inflation. Our

baseline specification for city-level price convergence is as follows:

$$\tilde{p}_{i,t} = \alpha + \beta_{-1}\tilde{p}_{i,t-1} + \beta_{\pi}\left(\tilde{p}_{i,t-1} \times \pi_t\right) + \beta_{war}\left(\tilde{p}_{i,t-1} \times war_{i,t}\right) + \beta_x'\mathbf{X}_i \times \tilde{p}_{i,t-1} + \gamma_t + \theta_i + \varepsilon_{i,t} \quad (4.8)$$

where $\tilde{p}_{i,t} := p_{i,t} - \overline{p_t}$ denotes the difference between city i's price (in log terms, same hereafter) and the national average at time t. π_t is calculated as the week-over-week change in the national average of rice or wheat prices. As noted in Section 3.2, the aggregate inflation dynamics of rice and wheat are quite similar, closely following the wholesale index during the years when all three prices coexisted. Therefore, how aggregate inflation is constructed is unlikely to affect the estimation results. In addition to inflation, we control for the potential effects of wars and trade frictions on the convergence of city-level prices. In our baseline estimation, the indicator $war_{i,t} = 1$ if one or more battles occurred within 50 kilometers of city i at time t. Our results are robust to alternative definitions of this variable. Time-invariant city characteristics $\mathbf{X}_i$ such as coastal access, railway access, terrain ruggedness, river density, soil suitability for rice or wheat, and the existence of treaty ports are defined and constructed similarly to those in Gao and Lei (2021). Details on these variables are relegated to Appendix C.3. We include week and city-level fixed effects to account for time- or city-specific factors influencing local prices in all exercises.

This specification is similar to previous studies testing the law of one price using regional price data (e.g., Parsley and Wei, 1996; Cecchetti, Mark and Sonora, 2002). City $i's$ price converges to the national average unconditionally when $0 < \beta_{-1} < 1$. A larger β_{-1} implies slower convergence. Besides, the collection of coefficients $(\beta_{\pi}, \beta_{war}, \beta_x)$ captures the impact of various factors on the speed of convergence. For instance, the effect of inflation on price convergence is reflected in β_{π}—a positive β_{π} suggests that higher inflation hinders price convergence, and vice versa. Similarly, β_{war} measures the impact of wars on price convergence. The intuition behind this indirect test is as follows: if, on average, a city's grain price converges toward the national average faster as inflation rises (i.e., $\beta_{\pi} < 0$), we would expect a negative correlation between price dispersion and inflation, conditional on past price dispersion. The linkage between convergence and dispersion can be (loosely) understood by applying a cross-sectional variance operator to both sides of Equation (4.8): a negative β_{π} indicates that π_t has a negative impact on the variance of $p_{i,t}$.

Table 2 presents the baseline estimates of key coefficients in Equation 4.8 across various sample periods, using rice and wheat price data separately. Our choice of different sample periods is driven by three concerns: fewer missing data since April 1942, a switch in the data source and frequency

Table 2: Price Convergence and Inflation

	Rice				*Wheat*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_{-1}	0.9209***	0.9181***	0.9174***	0.9171***	0.9195***	0.9162***	0.9142***	0.9083***
	(0.0080)	(0.0084)	(0.0090)	(0.0082)	(0.0106)	(0.0093)	(0.0108)	(0.0073)
β_{π}	-0.0015***	-0.0016***	-0.0015***	-0.0019***	-0.0010***	-0.0010***	-0.0009***	-0.0012***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
β_{war}	0.0153	0.0162*	0.0187*	0.0103	0.0225*	0.0231**	0.0246**	0.0237
	(0.0090)	(0.0091)	(0.0094)	(0.0189)	(0.0113)	(0.0111)	(0.0112)	(0.0145)
Constant	0.0211***	0.0205***	0.0255***	0.0217***	0.0210***	0.0199***	0.0308***	0.0204***
	(0.0021)	(0.0023)	(0.0035)	(0.0023)	(0.0022)	(0.0021)	(0.0043)	(0.0018)
City-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average π_t (%)	137.6	155.8	185.0	122.6	135.4	143.5	173.3	116.6
# of Obs.	42880	39862	26976	38219	25104	23334	15777	22454
adj. R^2	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98

Notes: This table reports the estimates of main coefficients in equation (4.8) and their robust standard errors clustered by province. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each specification uses either rice (1–4) or wheat (5–8) price data. Data frequency is weekly. Sample period: columns (1) and (5), April 1941–November 1948 (covering our entire sample); columns (2) and (6), April 1942–November 1948, a higher-quality subsample with fewer missing points; columns (3) and (7), July 1944–November 1948, a subsample with data available every two days; columns (4) and (8), April 1942–August 1948, a subsample omitting the post-currency reform period since August 1948. City-level control variables include $\tilde{p}_{i,t-1}$ interacted with terrain ruggedness, river density, soil suitability for rice or wheat, coastal access, treaty port and railway access. Both city and week fixed effects are considered. Average π_t presents the annualized weekly inflation rates in each sample period.

in July 1944, and the currency reform in August 1948. The parameter β_{-1} is estimated to be between 0.9 and 1, indicating an unconditional process of price convergence on average. However, the actual rate of convergence depends on the factors mentioned above (and their associated parameters). The primary parameter of interest is β_{π}, which determines how aggregate inflation affects price convergence. The main conclusion from this table is that β_{π} is consistently estimated to be significantly negative across samples, indicating that as inflation rises, city-level prices converge more quickly toward the aggregate—higher inflation is associated with lower price dispersion, conditional on past dispersion. Moreover, the estimates are similar in magnitudes, ranging between -0.0009 and -0.0019. To put this into perspective: based on the estimates in column (4), ceteris paribus, a one-standard-deviation increase in week-over-week aggregate inflation would lead to 3.8 percent reduction in the dispersion of log rice prices across the cities.[5]

β_{war} is consistently estimated to be positive across different samples, and, in most cases, it is

[5]Given that the standard deviation of nationwide weekly rice price inflation is 18.5, and using the estimates in Table 2 column (4), the percentage change in price dispersion due to a one-standard-deviation increase in nationwide inflation is calculated as:$-0.0019 \times 18.5/0.9171 = -3.8\%$.

also statistically significant. This result suggests that wars near a city significantly hinder price convergence across cities. This is not surprising, given that wars are likely to disrupt physical goods trade and communication infrastructure (information diffusion) across cities, both of which are proven important factors in understanding geographical dispersion of goods prices (e.g., Engel and Rogers, 1996; Gao and Lei, 2021).

GMM Estimates. Because T is fairly large in our weekly panel, the "Nickell" asymptotic bias of our within estimator is unlikely to be severe. Nonetheless, to mitigate concerns over this classic identification issue in linear dynamic panel models, we apply the difference GMM estimator proposed by Arellano and Bond (1991) and the system GMM estimator proposed by Blundell and Bond (1998). For difference GMM, lagged levels of the dependent variable are used as instruments in the first-differenced equation to form moment conditions. Unlike the within estimator, this estimator is consistent but may suffer from weak instruments. The Blundell-Bond estimator in a system GMM estimation addresses the weak instrument problem and improves performance in finite samples. We limit the number of lags used as instruments for both estimators to minimize the issue of having too many instruments.

Table 3 reports the results for our preferred sample period, April 1942 to August 1948, the same period used in columns (4) and (8) of Table 2. While the unconditional convergence coefficient β_{-1} can be sensitive to the choice of estimator, the primary coefficient of interest, β_{π}, remains consistent with the within estimates shown in columns (4) and (8) of Table 2. In the case of wheat, the GMM estimates are even larger in magnitude compared to the within estimates, suggesting a stronger negative impact of inflation on price dispersion across cities. Additionally, we report p-values for serial correlation tests in the first-differenced residuals of Equation (4.8) against the null of no serial correlation. We show that AR(2) can be rejected for the rice data, and AR(5) can be rejected for wheat, motivating the use of third or higher lags of the dependent variable as instruments for the former and the sixth or higher for the latter.

Robustness Check. We perform many robustness tests to further validate our baseline results across alternative definitions of variables and econometric specifications, as detailed in Appendix D.1. In Table D.1, we combine results from three alternative specifications of the baseline estimation: (i) using the simple arithmetic average of city-level grain prices to calculate nationwide inflation rates; (ii) including fixed effects and clustering the standard errors at different levels

Table 3: GMM Estimation

	Rice		*Wheat*	
	Arellano-Bond	Blundell-Bond	Arellano-Bond	Blundell-Bond
β_{-1}	0.8844***	0.9822***	0.9780***	0.9981***
	(0.0383)	(0.0095)	(0.0130)	(0.0101)
β_{π}	-0.0018***	-0.0019***	-0.0019***	-0.0021***
	(0.0002)	(0.0001)	(0.0004)	(0.0005)
β_{war}	0.2382*	0.0970	-0.0299	0.0872
	(0.1290)	(0.0925)	(0.0936)	(0.0669)
AR test p-value	0.338	0.891	0.882	0.878
# of Obs.	38098	38228	22320	22462

Notes: This table reports the estimates of the main coefficients of equation (4.8) using Arellano-Bond and Blundell-Bond estimators together with their robust standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each specification uses either rice or wheat price data. Data frequency is weekly. Sample period: April 1942–August 1948. As in the baseline, city-level control variables, city and week fixed effects are included. In the first two columns, we report AR(2) test of the first-differenced residuals and restrict the instrument set to lags 3 to 6; in the third and fourth, we report the AR(5) test results and restrict the instrument set to lags 6 to 9.

than is specified in the baseline; (iii) excluding cities with more than 80% missing observations throughout the estimation sample to address potential issues with unbalanced samples. Across these specifications, the results remain consistent with our baseline findings.

We also examine the nonlinear impact of inflation on price convergence rates by adding an inflation-squared term as an additional regressor in the baseline equation. As displayed in Table D.2, while the second-order term partially absorbs the first-order effect of inflation, both are estimated to be significantly negative. This suggests that the impact of inflation on price convergence and price dispersion becomes increasingly stronger in a high-inflation regime compared to a lower-inflation one. We now turn to an external validity test to further support this argument.

4.3 Comparison Between High and Low Inflation Times

As the majority of our sample period experienced high inflation, the conclusions drawn from our empirical exercises in previous sections are specific to high-inflation environments. But is there a difference in the price convergence and dispersion patterns between high- and low-inflation times? In Table 4, we provide suggestive evidence that these patterns can differ significantly during periods of low inflation. To arrive at this argument, we use a readily available rice price dataset from Gao and Lei (2021), covering 1870–1904, which was characterized by low inflation. We replicate our price convergence analysis using this data with a few adjustments. First, this dataset provides

Table 4: Price Convergence under Low Inflation

	High-Quality Rice	Medium-Quality Rice	Low-Quality Rice
$\hat{p}_{i,t-1}$	0.9912***	0.9956***	0.9987***
	(0.0111)	(0.0111)	(0.0168)
$\hat{p}_{i,t-1} \times \pi_t$	0.0068***	0.0071***	0.0074***
	(0.0008)	(0.0012)	(0.0018)
Average π_t (%)	0.203	0.193	-0.145
# of Obs.	46498	46498	40931

Notes: This table reports the estimates of main coefficients in equation (4.8) and their robust standard errors clustered by province using monthly rice price data in Gao and Lei (2021). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each column corresponds to a different type of price. Data frequency is monthly. Sample period: 1870–1904. Prefecture-level control variables include $\tilde{p}_{i,t-1}$ interacted with terrain ruggedness, river density, soil suitability for rice or wheat, coastal access, treaty port, and railway access. Both prefecture and month fixed effects are included. Average π_t presents the annualized monthly inflation rates for each rice category over the sample period.

more detailed prices for different rice categories (i.e., high-, medium-, and low-quality rice), which we examine separately. Second, since this period did not feature widespread wars, we omit the war variable. Third, the data is at the prefecture rather than the city level, and the frequency is monthly, compared to the weekly frequency in our baseline. Aside from these differences, we follow the baseline approach by including prefecture-level control variables and fixed effects.

Similar to the high-inflation environment, we also find unconditional price convergence across prefectures, though much slower, as indicated by the close-to-one estimate of β_{-1}. However, in contrast to the results in Table 2, the coefficient on the interaction term $\tilde{p}_{i,t-1} \times \pi_t$ is estimated to be significantly positive in the low-inflation environment, suggesting that as inflation goes up, price dispersion also rises—showing a markedly different effect compared to the high-inflation episode.

4.4 Inspecting the Mechanism

Information Channel. We have demonstrated that prices across cities converge more rapidly as inflation increases, leading to decreased price dispersion in a high-inflation environment. Conversely, this relationship reverses in low-inflation periods. To delve deeper into understanding these patterns, we analyze two distinct groups of cities: those located near major urban centers and those farther away. Specifically, we calculate the distance from each city to its nearest major city—defined as one of the ten largest cities[6] at the time—and classify cities as "Near" or "Far" based on whether they fall within the bottom or top quartile of the distance distribution across all cities.

[6]The ten largest cities in 1940s China were Shanghai, Chungking, Nanking, Tientsin, Peiping, Hankow, Canton, Tsingtao, Hsian, and Mukden (上海, 重庆, 南京, 天津, 北平, 汉口, 广州, 青岛, 西安, 沈阳, in Chinese).

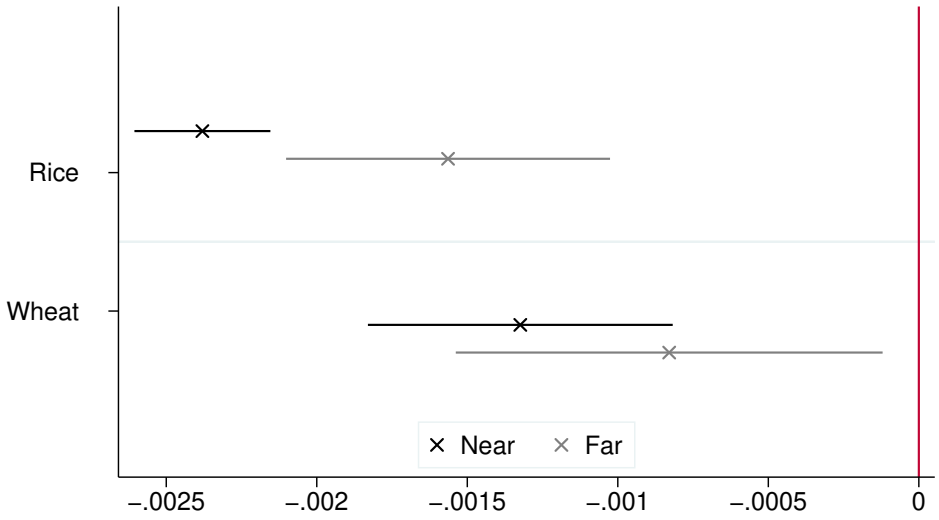
In addition to geographical distance, another distinguishing feature between these groups is the ease of acquiring information or, conversely, the level of information friction. Major cities typically benefit from better information infrastructure, such as newspapers, telegraphs, and radios, which enable more comprehensive news coverage. In contrast, more remote cities face greater challenges in accessing timely information due to the higher costs associated with establishing infrastructure over longer distances. Therefore, examining potential differences in convergence patterns between these two groups could help illuminate the role of information frictions in explaining our baseline results.

Figure 5 plots β_π estimates alongside their confidence intervals for the "Near" and "Far" groups of cities. Two key observations emerge. First, all coefficient estimates are significantly negative at the 90% confidence level, reinforcing our baseline findings within each subgroup. Second, the impact of rising inflation on price convergence is more pronounced for cities located closer to major urban centers. This pattern holds for both rice and wheat prices, although the difference in coefficients between the two groups is less statistically significant for wheat. Our interpretation aligns with the theoretical framework outlined in Section 2: higher information acquisition costs for remote cities impede price convergence, thereby exacerbating price dispersion.

Suggestive Evidence on "Attention to Inflation." We argue that information frictions may be crucial in explaining how inflation affects price dispersion across cities during periods of very high inflation. Our hypothesis to unravel this puzzle is that people's attention to inflation varies at different inflation levels. This idea resonates with recent studies exploring factors influencing consumer attention to inflation. For instance, Marcellino and Stevanovic (2022), Bracha and Tang (2024), and Korenok, Munro and Chen (2023) find that the attention to inflation, measured differently in each paper, tends to rise with inflation levels, particularly in recent episodes of high inflation.

To support our argument, we provide similar evidence using newspaper coverage of "prices" during our sample period as a proxy for public attention to price levels or changes. This approach is particularly relevant in our context, given that newspapers, along with radio and telegraphs, were the primary means of communicating important news and events during that era. These media reached a wide audience and provided content that could be relatively easily digitized for research. We digitize articles from three major newspapers of the 1940s, counting the occurrences of article titles directly related to inflation or prices. This data allows us to construct "attention to inflation"

Figure 5: Coefficient by Geographic Distance

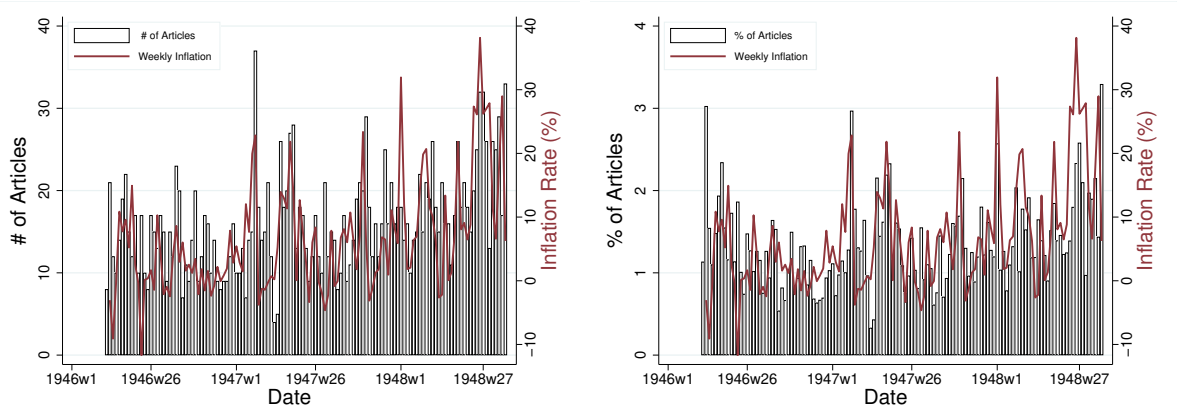


Notes: This figure displays the estimates of the coefficient β_π for two subgroups categorized by their distance to the nearest major city. Cities in the "Near" group fall within the bottom quartile of the distance distribution, while those in the "Far" group fall within the top quartile. The "x" markers represent the point estimates, and the lines indicate their 90% confidence intervals.

measures at daily frequencies, which are then aggregated to weekly frequencies and merged with our city-level inflation data.

In Figure 6, we present two attention measures derived from one of these newspapers, *Sin Wan Pao*—a Shanghai local news outlet—against the weekly wholesale price inflation in the city. The key observation is a strong comovement between inflation and the attention to price information. During each inflation peak, there was a significant surge in both the number and proportion of articles related to prices (broadly defined) relative to all news articles. This positive correlation holds consistently when we vary the scope of keyword searches or use data from alternative newspapers. Additional results are provided in Appendix D.2.

Figure 6: Newspaper Articles on "Prices" in Shanghai



Notes: These figures depict the weekly inflation in Shanghai, measured by the week-over-week change in wholesale prices, alongside the coverage of prices in the Shanghai local newspaper *Sin Wan Pao*. Coverage is quantified by the count of news titles containing keywords such as "price," "rice price," "grain price," "price index," "inflation," "living index," and "living expense index." The left graph displays the total number of occurrences of these titles, while the right graph shows the fraction of these titles relative to all news articles.

5 Conclusion

This paper revisits the relationship between price dispersion and inflation during periods of very high inflation. Using a novel, high-frequency, city-level grain price dataset from 1940s China, we provide robust evidence that, in a high-inflation environment, price dispersion decreases as inflation rises. Relatedly, city-level grain prices converged more quickly toward the national average as the inflation rate climbed. These findings contradict the predictions of standard monetary models regarding the relationship between price dispersion and inflation.

We illustrate our results with a pricing model incorporating state-dependent attention, where a firm's attention is influenced by the aggregate state, particularly the level of inflation. In this model, price dispersion is partly driven by endogenous attention; therefore, "attention to inflation" offers a new perspective on the relationship between inflation and price dispersion. Specifically, in a high-inflation regime, price dispersion can decrease as inflation rises, as opposed to the existing evidence focusing mainly on relatively low-inflation scenarios.

Our results have potential implications for the effectiveness of monetary policy under different inflation regimes. In a high-inflation environment, households, firms, and investors tend to pay more attention to the state of the economy. According to the information theory of monetary policy, this heightened attention could reduce the effectiveness of monetary interventions, making it more challenging for monetary policy alone to serve as an effective tool as inflation rises. While

we focus on a simple model to illustrate the factors influencing attention and price dispersion, a more comprehensive theory of state-dependent attention and a model with both information and nominal rigidity would be two potential avenues for research in the future.

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Online Appendix to "Attention to Inflation"

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A A Model of Endogenous Attention

A.1 Model Setup

We assume a nationwide representative household that consumes and supplies labor. The expected lifetime utility of households is given by

$$\mathbb{E}\sum_{t=0}^{\infty}\beta^t\left(\frac{C_t^{1-\gamma}}{1-\gamma}-\frac{N_t^{1+\nu}}{1+\nu}\right) \tag{A.1}$$

where labor supply N_t is normalized to 1; C_t is a CES aggregator of individual goods with an elasticity of substitution ε

$$C_t=\left[\int_0^1 (C_{it})^{\frac{\varepsilon-1}{\varepsilon}}di\right]^{\frac{\varepsilon}{\varepsilon-1}} \tag{A.2}$$

Each differentiated good i on the island is produced by a monopolistic competitive firm with production technology

$$Y_{it}=A_{it}N_{it}$$

where A_{it} captures the good/location-specific productivity shock. It follows that each producer i faces a demand curve derived from the household's optimal problem

$$Y_{it}=Y_t\left(\frac{P_{it}}{P_t}\right)^{-\varepsilon} \tag{A.3}$$

where P_{it} is the price of good i, Y_t is aggregate production that is in equilibrium equal to the aggregate demand C_t, and P_t is the aggregate price index

$$P_t=\left(\int_0^1 P_{it}^{1-\varepsilon}di\right)^{\frac{1}{1-\varepsilon}} \tag{A.4}$$

Money Supply. To close the model, we assume exogenous money supply $M_t = P_t Y_t$ that follows a random walk with drift $\bar{m}$:

$$m_t = m_{t-1} + \bar{m} + u_t,\ u_t \sim N(0, \sigma_m^2) \tag{A.5}$$

where $m_t \equiv \log M_t$.

Firm's Information Acquisition Problem. Individual firms face common nominal wage W_t. Each firm sets prices to maximize the discounted value of its real profits using the stochastic discount factor implied by the household's optimal problem:

$$\max_{P_{it}, Y_{it}} \mathbb{E} \sum_{t=0}^{\infty} \beta^t C_t^{-\gamma} \left(\frac{P_{it} Y_{it} - W_t \frac{Y_{it}}{A_{it}}}{P_t} \right) \text{ s.t. } (A.3) \tag{A.6}$$

In equilibrium, $C_t = Y_t$; so the payoff-relevant state for an individual firm is $z_{it} = (A_{it}, Z_t)$, where the aggregate payoff-relevant state $Z_t = (Y_t, P_t, W_t)$ is endogenously pinned down in equilibrium. To make the key problem transparent, we assume that decisions are separable across time, so the firm's optimization problem can be solved as a static problem. For ease of exposition, we define the risk-adjusted real profit as:

$$\Pi(P_i, z_i) = \frac{Y^{-\gamma}}{P} Y \left(\frac{P_i}{P} \right)^{-\varepsilon} \left(P_i - \frac{W}{A_i} \right)$$

Following Woodford (2003), we interpret $\Pi(P_i, z_i)$ as the financial-market valuation of the firm's random profit stream. Under perfect information, each firm takes aggregate condition (Y, P, W) as given and sets an optimal price $P_i^* = \frac{\varepsilon}{\varepsilon - 1} \frac{W}{A_i}$. Under imperfect information, it's helpful to make a second-order approximation of profit function Π around the optimal price and express it in terms of log prices:

$$\hat{\Pi}(p_i, z_i) = \Pi^*(z_i) - \frac{\varepsilon(\varepsilon - 1)}{2} \Pi^*(z_i) \left(p_i - p_i^* \right)^2 \tag{A.7}$$

where $p_i \equiv \log(P_i)$, $p_i^* \equiv \log(P_i^*)$. The derivation of (A.7) and expression of full-information profit $\Pi^*(z_i)$ are given in Appendix A.3.

To focus on the uncertainty about the aggregate state, we assume firm-level labor productivity A_i is fully observable. With imperfect information on the underlying state of the economy $z_i \in \mathcal{Z}$,

firms choose the precision of a Gaussian noisy signal s_i of the optimal price p_i^*, of which the cost is proportional to the Shannon mutual information. Specifically, the signal and prior distribution of p_i^* take the form

$$s_i = p_i^* + \frac{\epsilon_i}{\tau_i},\ \epsilon_i \sim N(0,1) \tag{A.8}$$

$$p_i^* \sim N(\bar{p}_i, \sigma^2_{p_i^*}) \tag{A.9}$$

where τ_i denotes the endogenous precision of signal s_i, which we call "attention"; $\bar{p}_i$ and $\sigma^2_{p_i^*}$ are the mean and variance of the prior distribution of optimal price p_i^*. As a result, the firm sets a price based on the posterior distribution of p_i^*, that is, $\hat{p}_i = \mathbb{E}(p_i^*|s_i)$. Choosing this signal s_i incurs a cost as specified in (2.4).

The firm's problem is to choose the signal precision to maximize its expected real profit net of the information cost, formalized as the following static problem:

$$\max_{\tau_i} \mathbb{E}_{p_i^*}\left[\mathbb{E}_{s_i}\left[-\frac{\varepsilon(\varepsilon-1)}{2}\Pi^*(z_i)\left(p_i^* - \mathbb{E}(p_i^*|s_i)\right)^2\right]\right] - \frac{1}{2}\lambda_i \log\left(1+\tau_i^2\sigma^2_{p_i^*}\right) \tag{A.10}$$

Equilibrium. An equilibrium of the model is a collection of island-level random processes for $(s_i, \hat{P}_i, \hat{Y}_i)$, aggregate price P, nominal wage W and real output Y such that:

1. Firms solve problem (A.10) given the law of motion for aggregate price P, wage W and output Y;

2. The equilibrium aggregate price P and wage W are consistent with idiosyncratic optimal decisions $\hat{P}_i$. In particular, $P = \left(\int \hat{P}_i^{1-\varepsilon} di\right)^{\frac{1}{1-\varepsilon}}$, and $W = Y^\gamma P$.

A.2 Model Solution

Optimal Attention. We now characterize and solve the firm's optimization problem. The firm's problem (A.10) can be simplified as:

$$\max_{\tau_i}\left(-\frac{\varepsilon(\varepsilon-1)}{2}\Pi^*(z_i)\sigma^2_{p_i^*|s_i} - \frac{1}{2}\lambda_i \log\left(1+\tau_i^2\sigma^2_{p_i^*}\right)\right) \tag{A.11}$$

where $\sigma^2_{p_i^*|s_i} = \frac{\sigma^2_{p_i^*}\frac{1}{\tau_i^2}}{\sigma^2_{p_i^*}+\frac{1}{\tau_i^2}} = \frac{\sigma^2_{p_i^*}}{\sigma^2_{p_i^*}\tau_i^2+1}$.

Take the F.O.C with respect to τ_i, we can solve for the optimal τ_i

$$\tau_i^* = \sqrt{\frac{\varepsilon(\varepsilon-1)\Pi^*(z_i)}{\lambda_i} - \frac{1}{\sigma^2_{p_i^*}}} \tag{A.12}$$

This simple analytic solution suggests that the optimal attention level τ_i^* depends on the cost of information λ_i, the prior variance of the optimal price $\sigma^2_{p_i^*}$, and the state z_i encoded in optimal price p_i^* and profit under full information Π^*. In particular,

1. Attention rises with optimal profit. Based on our derivation in A.3, the optimal profit under perfect information is determined by the aggregate demand and idiosyncratic productivity. As with pricing models with information frictions such as Lucas (1973), money is non-neutral, and a firm's profit rises with aggregate demand. As such, higher aggregate demand is associated with higher attention—the state-dependent attention that we highlight in this paper.

2. Attention decreases with information cost. It's clear from (A.12) that τ_i^* is smaller as λ_i increases. This is consistent with other rational inattention models.

3. Attention goes up when uncertainty is higher. Also consistent with existing theory, the higher the uncertainty about the optimal price, i.e., larger $\sigma^2_{p_i^*}$, the more attention firms pay to it.

Price Dispersion. Conditional on signal s_i, the firm's optimal pricing decision is to set a price equal to its posterior mean of the optimal price:

$$\hat{p}_i = \mathbb{E}(p_i^*|s_i) = \frac{\sigma^2_{p_i^*}}{\sigma^2_{p_i^*} + \frac{1}{\tau_i^2}}\left(p_i^* + \frac{\epsilon_i}{\tau_i}\right) + \left(1 - \frac{\sigma^2_{p_i^*}}{\sigma^2_{p_i^*} + \frac{1}{\tau_i^2}}\right)\bar{p}_i \tag{A.13}$$

Individual firm i's pricing equation (A.13) implies that the dispersion of prices is driven by not only idiosyncratic factors such as differences in regional productivity and heterogeneous cost of accessing information, etc., but also the precision of the noises, that is, the attention level. In

particular, cross-sectional price dispersion across firms can be written as:

$$\sigma^2_{\hat{p}_i} = \mathbb{VAR}\left[\frac{\sigma^2_{p_i^*}}{\sigma^2_{p_i^*}+\frac{1}{\tau_i^2}}p_i^* + \left(1-\frac{\sigma^2_{p_i^*}}{\sigma^2_{p_i^*}+\frac{1}{\tau_i^2}}\right)\bar{p}_i\right] + \mathbb{VAR}\left[\frac{\tau_i^*\epsilon_i}{\tau_i^{*2}+\frac{1}{\sigma^2_{p_i^*}}}\right] + \mathbb{COV}\left[\frac{\sigma^2_{p_i^*}}{\sigma^2_{p_i^*}+\frac{1}{\tau_i^2}}p_i^* + \left(1-\frac{\sigma^2_{p_i^*}}{\sigma^2_{p_i^*}+\frac{1}{\tau_i^2}}\right)\bar{p}_i, \frac{\tau_i^*\epsilon_i}{\left(\tau_i^{*2}+\frac{1}{\sigma^2_{p_i^*}}\right)}\right] \quad \text{(A.14)}$$

A.3 Derivation of Profit Function (A.7)

For simplicity, we omit the subscript t throughout the derivation. Risk-adjusted real profit is given by

$$\begin{aligned}\Pi(P_i, z_i) &= \frac{Y^{-\gamma}}{P}Y\left(\frac{P_i}{P}\right)^{-\varepsilon}\left(P_i - \frac{W}{A_i}\right)\\ &= Y^{1-\gamma}P^{\varepsilon-1}P_i^{-\varepsilon}\left(P_i - \frac{W}{A_i}\right)\end{aligned}$$

Substituting Y with M/P, we obtain

$$\Pi(P_i, z_i) = M^{1-\gamma}P^{\varepsilon+\gamma-2}P_i^{-\varepsilon}\left(P_i - \frac{W}{A_i}\right)$$

Label the term with P_i as $\tilde{\pi}_i = P_i^{-\varepsilon}\left(P_i - \frac{W}{A_i}\right)$. Ex-post optimal price, that is, optimal price under full information, is given by: $P_i^* = \frac{\varepsilon}{\varepsilon-1}\frac{W}{A_i}$. Denote the corresponding maximum profit $\Pi^*(z_i)$.

Next, we approximate the profit function at the second-order around P_i^*

$$\begin{aligned}\Pi(P_i, z_i) &\approx M^{1-\gamma}P^{\varepsilon+\gamma-2}\left[P_i^{*-\varepsilon}\left(P_i^* - \frac{W}{A_i}\right) + \left.\frac{\partial\tilde{\pi}_i}{\partial P_i}\right|_{P_i=P_i^*}(P_i - P_i^*) + \frac{1}{2}\left.\frac{\partial^2\tilde{\pi}_i}{\partial^2 P_i}\right|_{P_i=P_i^*}(P_i - P_i^*)^2\right]\\ &\approx M^{1-\gamma}P^{\varepsilon+\gamma-2}\left[\frac{1}{\varepsilon}P_i^{*1-\varepsilon} + \frac{1}{2}(1-\varepsilon)P_i^{*-\varepsilon-1}(P_i - P_i^*)^2\right]\end{aligned}$$

The first-order term drops out because of the first-order optimality condition. Summarize the constant and second-order terms, we rewrite the profit function as

$$\Pi(P_i, z_i) \approx \Pi^*(z_i) - \frac{1}{2}\Gamma(z_i)(P_i - P_i^*)^2 \quad \text{(A.15)}$$

where $\Pi^*(z_i) = \frac{1}{\varepsilon}M^{1-\gamma}P^{\varepsilon+\gamma-2}P_i^{*1-\varepsilon}$, $\Gamma(z_i) = (\varepsilon-1)M^{1-\gamma}P^{\varepsilon+\gamma-2}P_i^{*-\varepsilon-1}$. Rewrite these expres-

sions in terms of M, P, A_i only, using the equilibrium wage function $W_t = C_t^{\gamma} P_t = Y_t^{\gamma} P_t$:

$$\Pi^*(z_i) = \frac{1}{\varepsilon}\left(\frac{\varepsilon}{\varepsilon-1}\right)^{1-\varepsilon} M^{1-\gamma\varepsilon} P^{\gamma\varepsilon-2} A_i^{\varepsilon-1}$$
$$\Gamma(z_i) = (\varepsilon-1)\left(\frac{\varepsilon}{\varepsilon-1}\right)^{-1-\varepsilon} M^{1-2\gamma-\gamma\varepsilon} P^{\gamma\varepsilon+2\gamma-3} A_i^{\varepsilon+1}$$

We also observe that $\Gamma(z_i) = \varepsilon(\varepsilon-1)\frac{\Pi^*(z_i)}{P_i^{*2}}$, it follows that

$$\Pi(P_i, z_i) \approx \Pi^*(z_i) - \frac{1}{2}\varepsilon(\varepsilon-1)\Pi^*(z_i)\left(\frac{P_i - P_i^*}{P_i^*}\right)^2$$

Using the fact that $\frac{P_i - P_i^*}{P_i^*} \approx \log(P_i) - \log(P_i^*)$, we can rewrite the profit function $\Pi(P_i, z_i)$ in terms of log prices,

$$\hat{\Pi}(p_i, z_i) = \Pi^*(z_i) - \frac{\varepsilon(\varepsilon-1)}{2}\Pi^*(z_i)\,(p_i - p_i^*)^2$$

where $p_i \equiv \log(P_i)$, $p_i^* \equiv \log(P_i^*)$.

B Details on the Historical Background

B.1 The Timeline of Wars and Price Regulations

Our 1940s datasets encompass part of World War II and the entirety of the Chinese Civil War. In Figure B.1, we outline key events including the major price control policies implemented during this period of hyperinflation.

B.2 Price Regulation Policies and Their Failures

Chang (1958) discusses several price regulatory policies implemented during the hyperinflation period covered in our study. These include a reinforced price control program at the end of 1942, economic emergency measures in 1947, and the notable currency reform in 1948.

The November 1942 price regulation policies included measures such as price ceilings on daily necessities, rationing of consumer goods, government involvement in buying and selling commodities, restrictions on inventories and the use of scarce goods, and wage ceilings. However, these direct and indirect controls had minimal impact on curbing price escalation. First, the direct price



Figure B.1: Timeline of Events for Wars and Price Regulations

ceilings were applied to only a limited range of commodities in a few major cities, resulting in minimal nationwide effects. Second, government interventions like purchasing, selling, and rationing consumer goods had some influence on wholesale prices but little effect on retail prices due to inadequate and poorly coordinated administrative efforts. For instance, government transactions accounted for a negligible share of the total free-market supply of rice, exerting little influence on rice prices.

In February 1947, the government reintroduced similar price control policies. As before, their impact on prices was short-lived, lasting only about a month before prices surged again in April 1947. Regarding rice, fixed prices caused dealers to suspend rice markets, leading to widespread starvation, social unrest, and the eventual removal of rice price ceilings in early May.

In August 1948, the government enacted a freeze on prices and wages as part of a monetary reform that introduced the new currency, the Gold Yuan, which was defined as 0.2217 centigrams of pure gold. The new notes were exchanged at a rate of 1 to 3,000,000 in terms of the old fabi currency. Initially, strict enforcement maintained price stability for about six weeks in cities like Shanghai. However, in cities where enforcement was lax, inflation worsened. By late October, the price and wage ceilings were discontinued, just two months after their introduction.

Despite multiple attempts to regulate market prices during this hyperinflationary period, none of the efforts had a significant or lasting impact on consumer prices. Additionally, these policies had unintended consequences, such as market disruptions and social unrest, which led to their swift repeal, further undermining their effectiveness.

C Details on the Dataset

C.1 Grain Prices

Data Collection. We manually collect grain prices from archival sheets of three internal periodicals: the *Grain Briefs*, the *Grain Weekly Report*, and the *Grain Ten-Day Report*, published by the Ministry of Food under the Nationalist government. These periodicals, stored in microfilm or original paper format at the National Library of China, form a single publication series despite their different titles, with consecutive issue numbering.

From Issue 1 to Issue 89, the periodical *Grain Briefs* reports rice prices from April 1, 1941, to December 25, 1942, and wheat prices from April 30, 1941, to December 25, 1942. A typical archival spreadsheet in this periodical, as presented in Figure C.2, lists rice or wheat prices for

Figure C.2: A Sample in *Grain Brief*

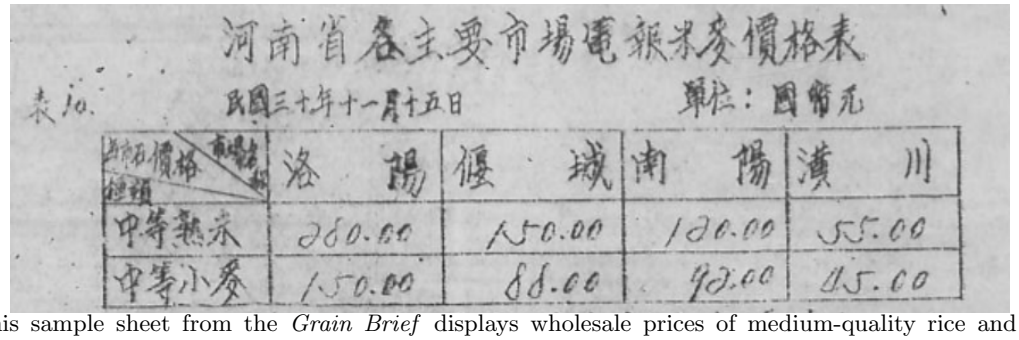

河南省各主要市場電報米麥價格表

表10. 民國三十年十一月十五日 單位：國幣元

品名	洛陽	偃城	南陽	漢川
中等熟米	280.00	150.00	120.00	55.00
中等小麥	150.00	88.00	92.00	45.00

Notes: This sample sheet from the *Grain Brief* displays wholesale prices of medium-quality rice and wheat for one *shidan* (市石, in Chinese, equivalent to 50kg) across grain markets in four cities in Henan province, China, on November 15, 1941. These prices were denominated in fabi yuan (国币元, in Chinese) and reported via telegraph.

selected cities on a given date.

From Issue 90 to Issue 168, the *Grain Weekly Report* covers daily grain prices from December 19, 1942, to June 30, 1944. As shown in Figure C.3, a typical archival spreadsheet from this periodical lists rice or wheat prices for 10 to 30 cities over seven consecutive dates within a week.

From Issue 169 to Issue 328, the *Grain Ten-Day Report* recorded prices every two days from July 2, 1944, to November 30, 1948. An archival spreadsheet typically lists rice or wheat prices for 20 to 40 cities on five alternative dates within a ten-day period, as depicted in Figure C.4. Issues 1 to 133 were handwritten and mimeographed, while issues 134 to 328 were typeset.

These grain prices are available only for cities under the Nationalist government's control from April 1941 to November 1948. Initially, prices were denominated in fabi currency; following the currency reform on August 19, 1948, they were recorded in units of Gold Yuan. For our empirical exercises, post-reform prices were converted back to fabi using a conversion rate of 1 Gold Yuan to 3,000,000 fabi.

Data Availability. While grain prices are available for 314 cities (270 for rice and 239 for wheat) at least once between April 1941 and November 1948, data availability at each city varies over time due to changes in the Nationalist government's capacity and territorial control during the wartime as well as the change in our data source.

The Ministry of Food initially compiled the *Grain Briefs* using data from the *Telegrams on Grain*, which focused on the Sichuan province-Chungking city region, documenting rice and wheat prices for only about 60 and 30 cities, respectively. However, by mid-1942 (starting with the 59th issue), its coverage expanded significantly to include nearly all provinces under Nationalist control.

Since February 13, 1943, the *Grain Weekly Report* ceased reporting wheat prices in several

Figure C.3: A Sample in *Grain Weekly Report*



Notes: The two tables on this sample sheet from the *Grain Weekly Report* present wholesale prices of medium-quality rice and wheat for one *shidan* (市石, in Chinese, equivalent to 50kg) across grain markets in multiple cities in Shaanxi and Shanxi provinces, China, from May 1 to 7, 1943. These prices were denominated in fabi yuan (国币元, in Chinese) and reported via telegraph. The tables also report average prices for the current and previous weeks, along with percentage changes.

southern regions, reducing the number of cities covered. On July 2, 1944 (the 169th issue), the *Grain Weekly Report* changed its name to the *Grain Ten-Day Report* and resumed documenting wheat prices in some southern regions. However, due to a special edition on the grain situation in the first half of 1944 (the 171st issue), grain price reporting was sparse in late July 1944, as depicted in Figure C.6. Following the unfavorable events of the Sino-Japanese War (Operation Ichi-Go, or the Battle of Henan-Hunan-Guangxi), rice price reporting in provinces such as Guangxi, Guangdong, Zhejiang, and Anhui was discontinued after September 1944 (the 175th issue). However, following the end of World War II in August 1945 (the 208th issue), the reporting of rice prices gradually resumed and expanded to include areas previously under Japanese occupation.

Figure C.5 presents two snapshots of our data coverage. In this figure, the green, red, and blue colors represent cities where only rice prices, only wheat prices, and both rice and wheat prices are available, respectively. Due to the impact of wars, our dataset captures fewer cities in the 1944 sample compared to the 1946 one. Figure C.6 summarizes the number of cities with available grain

Figure C.4: A Sample in *Grain Ten-Day Report*



表一：　中國各重要糧食市場中等熟米價格統計表

三十七年十一月上旬　　單位：每市石金圓券

省別	市場名稱	二日	四日	六日	八日	十日	本旬平均價	上旬平均價	本旬與上旬之比較
特別市	南京市	40.00	……	……	……	……	……	……	……
	上海市	80.00	90.00	200.00	……	……	……	……	……
	廣州市	64.06	72.00	96.00	161.60	256.00	129.92	29.60	+ 100.32
	漢口市	150.00	120.00	120.00	260.00	320.00	194.00	64.40	+ 129.60
	重慶市	29.00	33.00	46.00	51.00	68.00	46.60	21.92	+ 24.68
	北平市	……	291.20	240.00	240.00	224.00	248.80	……	……
	天津市	……	……	256.00	264.00	320.00	280.00	267.20	+ 18.60
	瀋陽市	……	……	……	……	……	……	……	……
	青島市	320.00	320.00	430.00	480.00	640.00	432.00	326.40	+ 105.60
	西安市	100.00	100.00	100.00	130.00	120.00	110.00	……	……
江蘇省	鎮江	……	……	……	……	……	……	……	……
	武進	……	……	165.00	……	380.00	……	……	……
	無錫	……	……	……	……	……	……	……	……
	吳縣	70.00	90.00	……	……	……	……	……	……
	常熟	……	……	120.00	……	……	……	……	……
	松江	……	……	……	……	585.00	……	……	……
	南通	……	……	……	……	……	……	……	……
	江都	……	……	……	……	……	……	……	……
	銅山	……	……	……	……	……	……	……	……
	淮陰	……	……	……	……	……	……	……	……
浙江省	杭州市	……	……	……	……	……	……	……	……
	嘉興	78.00	84.00	138.00	156.00	390.00	169.20	……	……
	吳興	70.00	72.00	100.00	150.00	280.00	134.40	……	……
	海寧硤石	……	……	85.00	……	350.00	……	……	……
	紹興	……	……	130.00	……	300.00	……	……	……
	鄞縣	88.00	82.00	105.00	175.00	260.00	142.00	……	……
	金華	……	……	……	……	……	……	……	……
	臨海	……	……	60.00	……	160.00	……	……	……
	永嘉	62.74	76.10	76.10	99.33	177.77	98.41	……	……
	衢縣	……	……	35.41	……	35.41	……	……	……
江西省	南昌市	45.00	43.00	55.00	123.00	130.00	79.20	28.00	+ 51.20
	九江	50.00	50.00	80.00	120.00	180.00	96.00	……	……
	浮梁	48.00	……	60.00	……	80.00	62.67	36.00	+ 26.67
	上饒	……	……	100.00	……	270.00	……	……	……
	贛縣	50.00	……	70.00	……	200.00	106.67	34.00	+ 72.67
	臨川	43.00	……	66.00	……	90.00	66.33	30.00	+ 36.33
	吉安	30.00	……	40.00	……	75.00	48.33	25.00	+ 23.33
	贛縣	42.60	44.00	47.40	55.03	91.00	56.20	43.58	+ 13.62
	萍鄉	42.58	……	58.50	……	90.00	63.50	25.00	+ 38.50

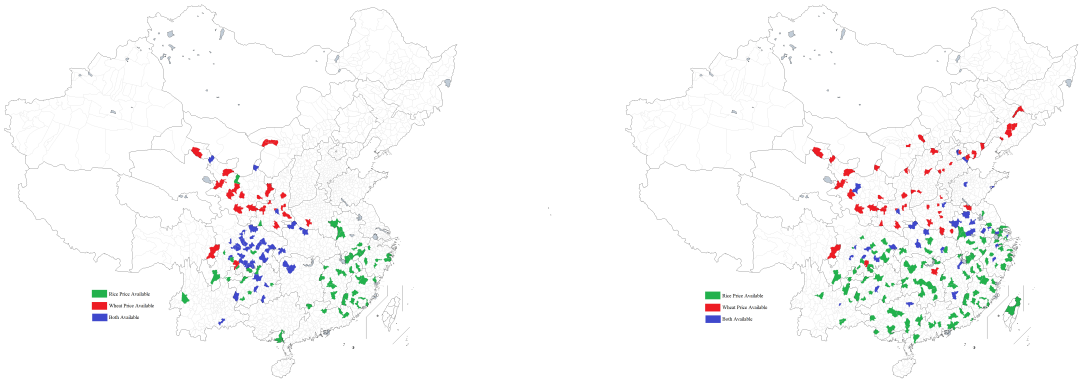
Notes: This sample sheet from *Grain Ten-Day Report* displays wholesale prices of medium-quality rice for one *shidan* (市石, in Chinese, equivalent to 50kg) across grain markets in numerous cities across multiple provinces of China during the first ten days (上旬, in Chinese) of November 1 to 10, 1948. These prices were denominated in *Gold Yuan Certificate* (金圓券, in Chinese) and reported every other day. The tables also include average prices for the current ten days (本旬) and the previous ten days (上旬), along with their percentage changes.

prices each week. On average, approximately 100 cities reported rice prices throughout the period, with 60 cities before April 1942, increasing to 107 afterward. Similarly, around 60 cities reported wheat prices, with 37 cities before April 1942 and 63 afterward.

C.2 Battlefields

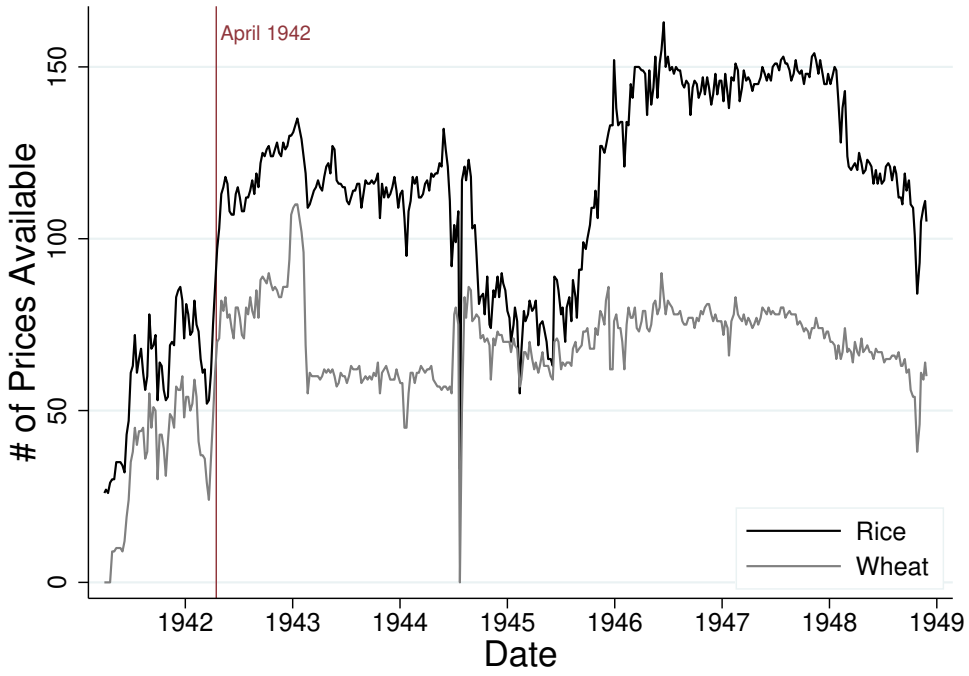
To control for the potential effects of wars on our main analysis, we construct a dataset containing spatiotemporal information on 145 major battles during our sample period. Of these, 40 battles occurred during the World War II period (April 1941 to August 1945), as documented in *The Frontal Battlefield Operations in China's War of Resistance Against Japanese Aggression*, and 105 took place during the Civil War (September 10, 1945, to November 30, 1948), as recorded in *The*

Figure C.5: Available Data on Rice and Wheat Prices



Notes: These figures display the cities covered by our samples for November 1944 (left) and November 1946 (right). These two months serve as representative samples from the World War II and Civil War periods.

Figure C.6: Number of Observations Each Week



Notes: The figure shows the weekly number of observed prices for rice and wheat.

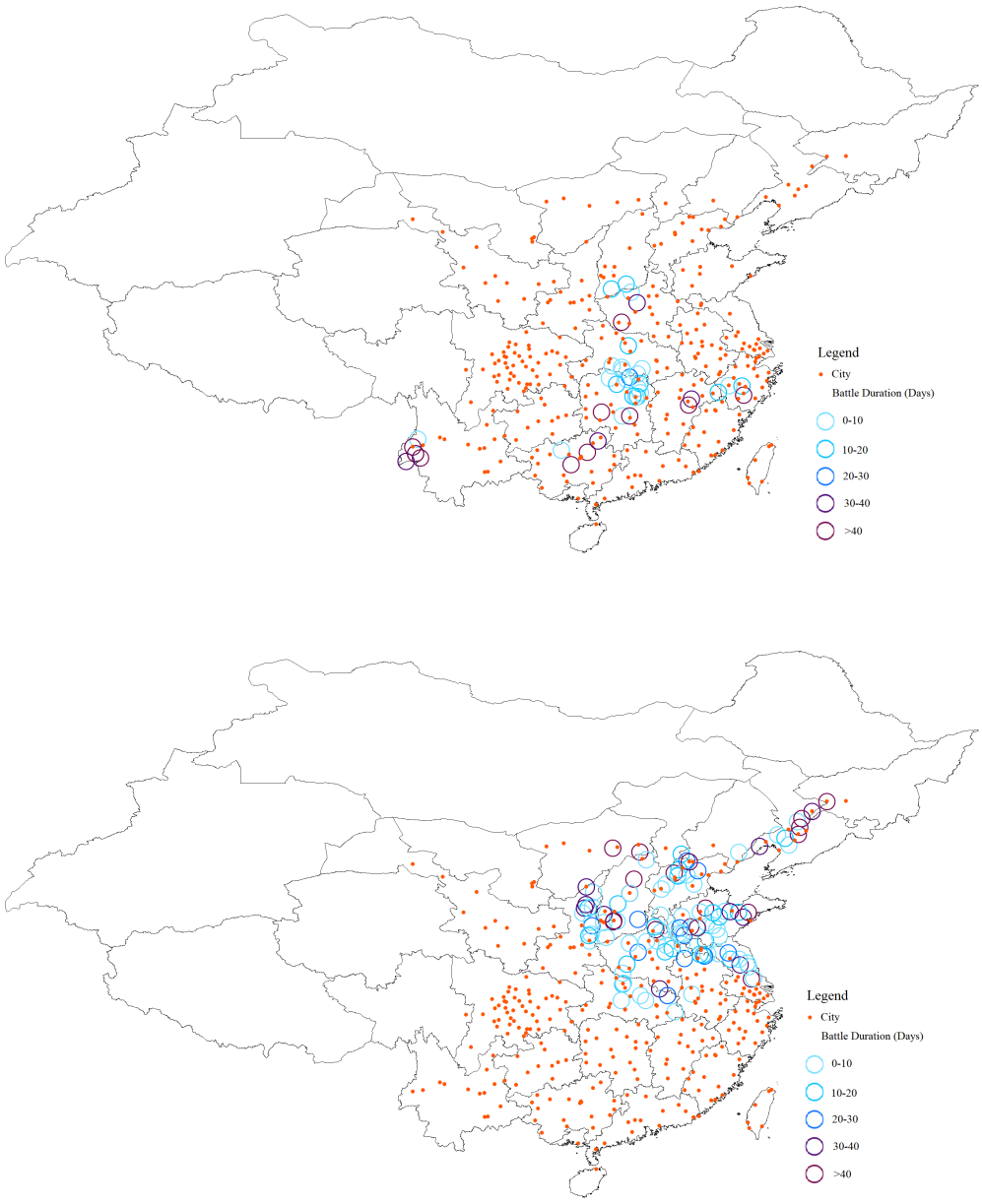
History of the Chinese People's Liberation Army (1945-1949). If a very large battle is divided into phases in the records, each phase is counted separately.

For each battle, we document its duration (start and end dates) and primary location. The central location of a battle is determined by the arithmetic or weighted average[7] of the longitudes

[7]The weight of each city is based on the word count of its name in the battle record.

and latitudes of the cities or counties primarily involved. Figure C.7 depicts the duration and geographic distribution of major battles from these two wars, along with the locations of all 314 cities in our sample.

Figure C.7: Major Battles



Notes: This figure presents the major battles considered in our empirical analysis during the two war periods, World War II (left, 1941–1945) and the Civil War (right, 1945–1948). Data source: *The Frontal Battlefield Operations in China's War of Resistance Against Japanese Aggression* and *The History of the Chinese People's Liberation Army (1945-1949)*.

C.3 City Characteristics

We collect city characteristics as control variables in our empirical analysis, due to their potential impacts on price convergence across cities. These variables include coastal access, railway access, terrain ruggedness, river density, soil suitability for rice or wheat, and the existence of treaty ports. The definitions of these variables and their data sources are described as follows.

Coast Access is a dummy variable that equals one for cities located on the coast. *Railway Access* is a dummy variable that equals one if a train station existed in the city from 1941 to 1948. Data source: Zhang (1997). *Terrain Ruggedness* is calculated as the standard deviation of elevations within 20 kilometers of the city's administrative center. Data source: USGS (2018) for elevation, Amap (AutoNavi) for the location (geographical coordinates) of the city governments. *River Density* is the density of navigable river channels within 20 kilometers of the city's administrative center, measured in decimal latitude and longitude units. Data source: National 1:250000 Three-Level River Basin Data Set from the National Cryosphere Desert Data Center `www.ncdc.ac.cn`. *Soil Suitability for Rice or Wheat* is the average suitability of soil within 20 kilometers of the city's administrative center. Data source: Fischer et al. (2012). *Treaty Port* is a dummy variable that equals one if the city was a treaty port or a subordinate jurisdiction of a treaty port. Data source: Yan (2016).

C.4 Newspaper Coverage

According to Hu (1998), in the 1940s, *Shun Pao*, *Sin Wan Pao*, and *Ta Kung Pao* (申报, 新闻报, and 大公报, in Chinese) were the three newspapers with the largest circulation in Shanghai, followed by *Central Daily News* (中央日报), the official newspaper of the Nationalist Party of China. This section provides an overview of the coverage of these newspapers and describes how we measure attention to inflation using a text analysis approach.

The Shun Pao was published in Shanghai from April 1872 to May 1949, producing 25,600 issues over 77 years, making it one of the most influential newspapers in the late 1800s and early 1900s. It was often regarded as the Chinese equivalent of *The Times* or *The New York Times*. In the 1930s, Shun Pao maintained wide circulation across China. According to its internal archives, *An Overview of Shun Pao* (Shun Pao Press, 2014), in 1934, the newspaper had been distributed across 27 provinces and internationally, with a total circulation of 155,900 copies. Shanghai had the highest distribution, followed by Jiangsu and Zhejiang.

The Sin Wan Pao was published from February 1893 to May 1949 and was equally popular as Shun Pao in Shanghai and other parts of China. *An Overview of Sin Wan Pao* in *Shanghai Archives* documents that Sin Wan Pao was circulated across 22 provinces and internationally in 1930, with a total distribution of 150,028 copies, comparable to Shun Pao. Shanghai had the largest circulation, followed by Jiangsu and Zhejiang.

Ta Kung Pao was founded in Tianjin in 1902. During the Second Sino-Japanese War, the newspaper's staff fled to Shanghai, Hankou, Chungking, Guilin, and Hong Kong to continue publishing. It is still published today in Hong Kong, making it the oldest active Chinese-language newspaper in China. According to Cai and Hui (2017), Ta Kung Pao's publishing branch in Chungking City maintained a regular circulation of over 60,000 copies in the 1940s, sometimes reaching up to 100,000. [8]

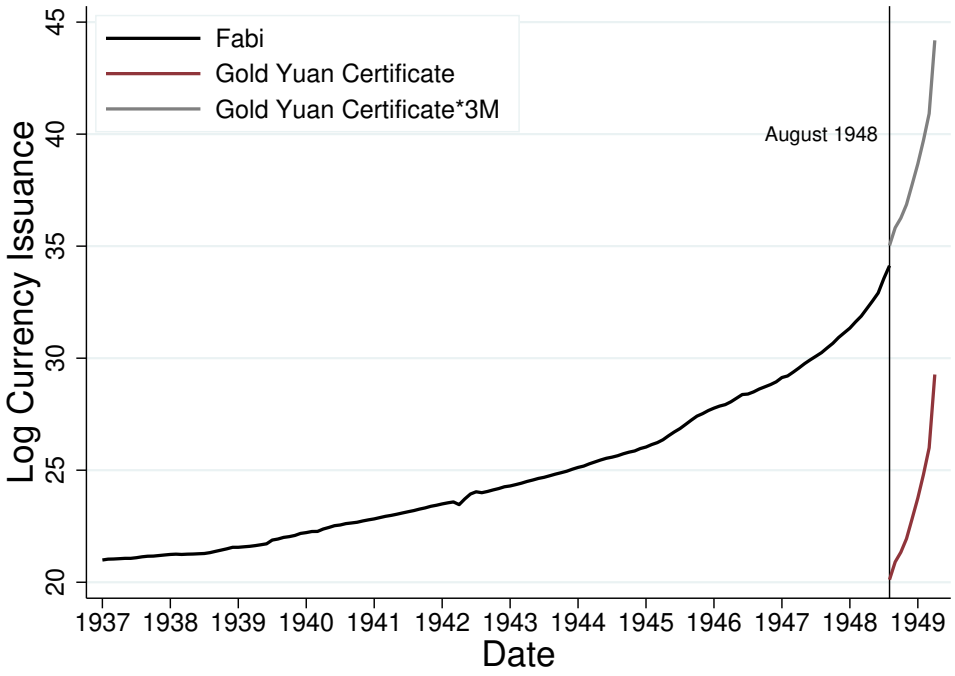
Given the popularity of these newspapers, we use article counts to measure how public attention to inflation varied over time. Specifically, we access the full-text databases of Shun Pao, Ta Kung Pao, and Sin Wan Pao through *Chinese Modern Press* published by Get-Hong Communication Co., and *National Newspaper Index, Xinwenbao* published by Quanguo Baokan Suoyin Editorial Office. From November 1945 to April 1949, we search these newspapers using keywords such as "general price levels (物价)," "prices (价格)," "grain prices (粮价)," "rice prices (米价)," "price indices (物价/价格指数)," "inflation (通货膨胀)," and "cost of living indices (生活费指数)." We then count the number of news articles containing any of these keywords in their headlines, titles, charts, or main texts. As shown in Figure 6 in Subsection 4.4 and additional figures in Appendix D.2, we present both the number of article titles containing these terms and the proportion of these articles relative to the total daily articles as measures of public attention to inflation.

C.5 Money Supply

Wu (1958) documents monthly currency issuance from January 1937 to April 1949. As aforementioned, the National Government issued fabi as the legal tender before the currency reform on August 19, 1948, after which the Gold Yuan Certificate was introduced. Figure C.8 displays the log-scaled money supply patterns in both currency denominations (in yuan). For the Gold Yuan, the figure displays both the original and adjusted issuance amounts, with the latter multiplied by three million (the conversion rate between the two currencies) to ensure continuity with the

[8] Cai and Hui (2017) also document the circulation of other prominent newspapers in Chungking at the time, such as *Sin Min Pao* (新民报) with 40,000 copies, *Xinhua Daily* (新华日报) with 22,000 copies, and *Business Daily* (商务日报) with 10,000 copies.

Figure C.8: Money Supply



Notes: This figure presents the log-scaled monthly money supply (in yuan) from January 1937 to April 1949. The vertical line in August 1948 marks the currency reform that replaced the fabi with the Gold Yuan. Before the reform, the black line represents fabi circulation. After the reform, the figure shows the original Gold Yuan issuance (red line) and the adjusted issuance (gray line), multiplied by three million to maintain continuity with the fabi data. Source: Wu (1958)

previously reported fabi issuance amounts. As of January 1937, the fabi stock was 1.31 billion yuan, and by August 21, 1948, the amount in circulation had ballooned to over 663 trillion yuan. The devaluation of the Gold Yuan Certificate was even more severe. As of August 31, 1948, 544 million Gold Yuan were issued (compared to the 2 billion limit promised at the start of the currency reform), but within seven months, the issuance had skyrocketed to 516 billion.

D Additional Empirical Results

D.1 Robustness Tests

Table D.1: Alternative Robustness Tests

	Rice			*Wheat*		
	(1)	(2)	(3)	(4)	(5)	(6)
β_{-1}	0.9181***	0.9836***	0.9156***	0.9105***	0.9854***	0.9211***
	(0.0091)	(0.0035)	(0.0084)	(0.0079)	(0.0029)	(0.0074)
β_{π}	-0.0022***	-0.0019***	-0.0019***	-0.0017***	-0.0012***	-0.0014***
	(0.0002)	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
β_{war}	0.0020	0.0080	0.0140	0.0243	0.0251*	0.0276*
	(0.0170)	(0.0284)	(0.0228)	(0.0150)	(0.0141)	(0.0138)
Constant	0.0040**	0.0146***	0.0213***	0.0021	0.0112***	0.0174***
	(0.0018)	(0.0017)	(0.0022)	(0.0015)	(0.0022)	(0.0017)
City-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	No	Yes	Yes	No	Yes
Province FE	No	Yes	No	No	Yes	No
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	38219	38228	36648	22454	22462	14133
adj. R^2	0.98	0.98	0.98	0.97	0.97	0.97

Notes: This table reports the estimates of main coefficients in equation (4.8) and their robust standard errors across three robustness tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each specification uses either rice (1–3) or wheat (4–6) price data. Data frequency is weekly. Sample period: April 1942–August 1948. City-level control variables include $\hat{p}_{i,t-1}$ interacted with terrain ruggedness, river density, soil suitability for rice or wheat, coastal access, treaty port and railway access. In (1) and (4), nationwide price level is calculated as the simple arithmetic average of city-level prices, instead of the population weighted average as in our baseline measure. In (2) and (5), we include fixed effects at the province level and cluster the standard errors by city. In contrast, for the other columns, we follow the baseline practice by including fixed effects at the city level and clustering the standard errors by province. In (3) and (6), we remove cities with more than 80% missing data from our estimation sample.

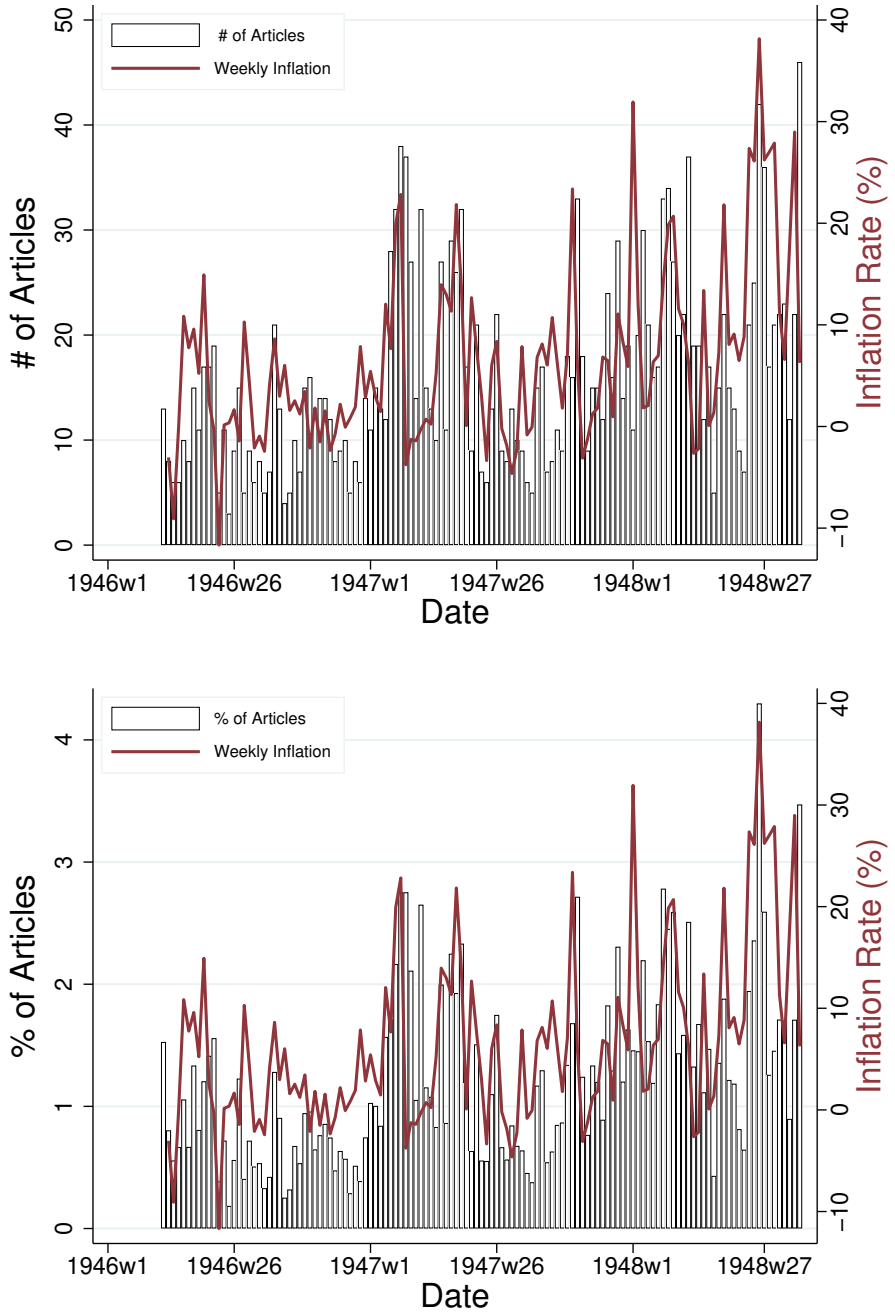
Table D.2: Nonlinear Effects of Inflation

	(1)	(2)
$\tilde{p}_{i,t-1}$	0.9207***	0.9099***
	(0.0079)	(0.0077)
$\tilde{p}_{i,t-1} \times \pi_t$	-0.0010***	-0.0007***
	(0.0002)	(0.0002)
$\tilde{p}_{i,t-1} \times \pi_t^2$	-1.49×10^{-5}***	-1.17×10^{-5}***
	(1.28×10^{-6})	(1.79×10^{-6})
$\tilde{p}_{i,t-1} \times \text{war}_{i,t}$	0.0083	0.0220
	(0.0171)	(0.0148)
Constant	0.0216***	0.0220***
	(0.0020)	(0.0017)
City-Level Controls	Yes	Yes
City FE	Yes	Yes
Week FE	Yes	Yes
# of Obs.	38219	22454
adj. R^2	0.98	0.98

Notes: This table reports the coefficient estimates and their robust standard errors clustered by province. The specification is the same as in Table 2, except that an inflation-squared term is added as an additional regressor to capture the nonlinear impact of inflation on price convergence. Columns (1) and (2) correspond to rice and wheat, respectively. Sample period: April 1942–August 1948.

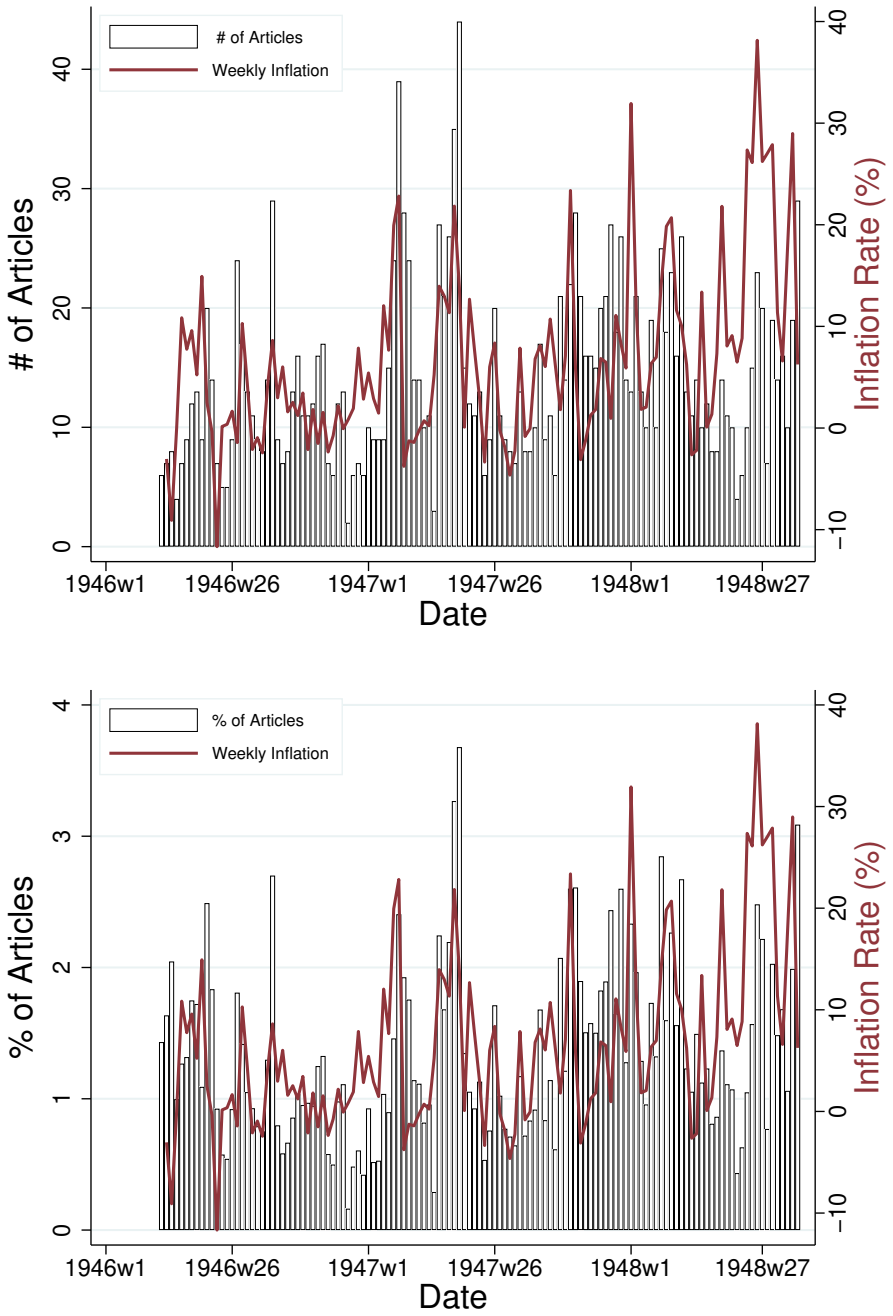
D.2 Newspaper Coverage

Figure D.9: Newspaper Articles on "Prices" in Shun Pao



Notes: These figures plot the weekly inflation in Shanghai, measured by the week-over-week change in wholesale prices, against the coverage of prices in the newspaper outlet *Shun Pao*. This coverage is quantified by the number of news titles that include terms such as "price," "rice price," "grain price," "price index," "inflation," "living index," and "living expense index." The top figure shows the total number of such titles, while the bottom figure displays the fraction of these titles among all news articles.

Figure D.10: Newspaper Articles on "Prices" in Ta Kung Pao



Notes: These figures depict weekly inflation in Shanghai, calculated as the week-over-week change in wholesale prices, alongside the coverage of price-related topics in the newspaper outlet *Ta Kung Pao*. The coverage is quantified by the number of news titles containing terms such as "price," "rice price," "grain price," "price index," "inflation," "living index," and "living expense index." The top figure shows the total count of these titles, while the bottom figure displays the fraction of these titles relative to all news articles.

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