

Attention to Inflation*

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Preliminary Draft

Abstract

We study pricing behaviors when inflation is very high using a new data set of high-frequency city-level grain prices in 1940s China. We find that city-level prices converged more rapidly to the national average as inflation soared, which reduced price dispersion. This unconventional empirical relationship is explained with a pricing model incorporating state-dependent *attention to inflation*, whereby individuals pay greater attention to overall prices as inflation rises, thus altering the relationship between inflation and price dispersion. We provide suggestive evidence that supports this theory. Overall, our paper sheds light on a novel aspect of price setting that has broader implications for monetary policy in a high inflationary environment.

Keywords: Hyperinflation; price dispersion; rational inattention

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. Former Chairman Alan Greenspan put it this way: “For all practical purposes, price stability means that expected changes in the average price level are small enough and gradual enough that they do not materially enter business and household financial decisions.”

Jerome H. Powell, Jackson Hole Symposium, August 2022

1 Introduction

In standard New Keynesian models, the welfare cost of inflation comes from (inefficient) price dispersion, which is the central determinant of 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 papers that study this relationship focused on low inflation levels, which is the norm in history (e.g., [Sheremirov, 2020](#)). This study explores the relationship between aggregate inflation and price dispersion when inflation is very high or hyperinflation. It is an important and relevant topic as an increasing number of countries have been experiencing very high inflation rates since the pandemic.

To do so, we use a unique high-frequency historical data set of grain prices at the city level during the hyperinflation period of 1940s China. It allows us to study price-setting behaviors both at the micro level and at a very high frequency. Our empirical result shows a negative inflation-price dispersion relationship—city-level prices converge faster to the national mean as inflation increases. In turn, the price dispersion tends to be smaller when aggregate inflation increases in an environment with very high inflation. This result holds even when we account for potential confounding factors such as wars that impede information or goods flow and communication networks such as telegraphs and telephone lines that may reduce information frictions. We conducted various robustness tests and confirmed the validity of this result.

The empirical result challenges standard macro models that typically imply a positive relationship between the two (e.g., [Nakamura et al., 2018](#); [Alvarez et al., 2019](#)). Our interpretation of this

result is the oft-neglected role of inattention to macro events. The idea is as follows. Acquiring noisy information about the aggregate economy, particularly aggregate prices, is costly for an individual firm, especially for our study period. When inflation is low, the firm pays little attention to the aggregate price level, as the cost of misoptimizing can be inconsequential. However, this cost can be enormous during high inflation or hyperinflation episodes. Therefore, firms closely monitor price signals and choose to keep up with aggregate inflation, the market’s average outcome of price settings.

We model the attention problem using a stochastic choice framework that gives analytical results. In the model, agents face a problem of costly control, and they pick stochastic choice rules that maximize the expected profits minus the cognitive costs associated with more precise decisions (relative to the ex-post optimum). We utilize this model to test the hypothesis: Do agents pay more or less attention when inflation is high? Is the price dispersion higher or lower as inflation goes up? Our model implies that, under certain reasonable parametric assumptions, firms pay more attention to aggregate conditions when inflation and the cost of misoptimization are higher. As a result, price dispersion is lower when inflation increases because of the higher attention and lower misoptimization for all firms. This state-dependent attention to inflation shares a similar feature with recent literature on inattention in the macroeconomy, such as [Flynn and Sastry \(2022\)](#).

To provide additional supporting evidence of our attention theory, we gathered the newspaper data on the coverage of price information as a proxy for the public’s attention to inflation, including the appearances of “price,” “inflation,” “living costs” and other similar terms that relate to prices in the headline or/and primary texts, an approach similar to recent literature such as [Song and Stern \(2023\)](#); [Flynn and Sastry \(2022\)](#). Our text-based attention measure comoved strongly to inflation itself, regardless of the newspaper we look at, how we measure attention in the data, and which city we focus on. This finding also echoes some recent papers using the Google search index and newspaper coverage of prices to establish the link between attention and inflation.

We make three primary contributions to the literature. First, we build a novel and comprehensive city-level price data set (together with other micro-level variables such as wars and telecommunications) in 1940s China. Other scholars can apply these data to interesting macroeconomics and economic history questions. Second, we establish a vastly different relationship between aggregate inflation and price dispersion when inflation is very high, which poses a threat to standard New Keynesian macro models and their positive and normative implications for monetary policy. Finally, we build a novel theory with costly information and state-dependent attention allocation that

is parsimonious but powerful to help us explain the empirical findings. Our model suggests that state-dependent attention plays a non-negligible role in understanding a firm’s pricing decision, and its importance is especially pronounced when inflation is high and volatile.

Literature. Our paper is related to the following two strands of literature in macroeconomics. First, a voluminous literature in monetary economics studies price-setting behaviors and price dispersion, but mostly in low-inflation environments (with the exception that [Alvarez et al. \(2019\)](#) and [Gagnon \(2009\)](#) study the relationship between inflation and individual price setting during the high inflation episodes in Argentina and Mexico respectively). For example, [Reinsdorf \(1994\)](#) finds that price dispersion rose when inflation fell using BLS microdata. [Nakamura et al. \(2018\)](#) find no big change in price dispersion as inflation went up during the Great Inflation era in the U.S. and argue that menu cost model predictions align better with these results than the Calvo model. [Sheremirov \(2020\)](#) finds that price dispersion rises with inflation for the low inflation period of 2002–2012. Using scanner data on retail product prices, [Sara-Zaror \(2021\)](#) documents that price dispersion of identical goods increases steeply around zero inflation and becomes flatter as inflation increases. In Section A, we review these standard monetary models, i.e., Calvo pricing model, menu-cost model and information friction models. We make the point that this relationship can flip sign as inflation becomes very high, which cannot be explained by these standard pricing models.

Second, our theoretical interpretation of the empirical results is built upon the literature on the role of attention in understanding macro dynamics, in particular in price setting (e.g., [Sims, 2003](#); [Reis, 2006](#); [Maćkowiak and Wiederholt, 2009](#); [Alvarez, Lippi and Paciello, 2016](#)). Our state-dependent attention framework is especially related to recent work by [Flynn and Sastry \(2022\)](#), [Flynn and Sastry \(2021\)](#), and [Turen \(2023\)](#), which model attention as being dependent on the underlying state of the economy. Unlike previous works, our theoretical model explains explicitly why the level of inflation itself might matter for attention to inflation itself, an observation supported by recent empirical studies including [Weber et al. \(2023\)](#) and [Bracha and Tang \(2022\)](#), while in previous models, it’s the uncertainty of economic fundamentals that drives the state-dependent attention allocation.

2 A Model of Attention to Inflation

2.1 Traditional Pricing 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 remain unchanged each period, dispersion of log prices $\Delta_t \equiv \text{var}_i[\log p_t(i)]$ can be solved in closed form (see, [Woodford, 2003b](#) 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 by 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 very different 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 higher dispersion of prices.¹

Information frictions models, in particular those featuring noisy signals, also generate price dispersion. However, they do not typically predict a relationship between price dispersion and aggregate inflation as dispersion is mainly driven by volatility of the aggregate state and precision of the price signals. A discussion of price dispersion in such models is relegated to [Appendix A](#).

Taken together, under a high-inflation environment, traditional pricing models predict that price dispersion is nondecreasing with inflation. In [Section 4](#), we test whether this prediction holds in our empirical context. Before that, we provide a theory featuring costly information acquisition that has a different implication.

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.

2.2 State-Dependent Attention

Model Setup. In this part, we provide a parsimonious theory of pricing with information frictions, that is, firms (representative in each city, which is analogous to the famous island model by Lucas, 1973) have limited capacity to understand the aggregate state of the economy. Instead, they must pay information costs to obtain more precise signals and make more precise optimization decisions. We aim to theoretically show how the cost of misoptimizing varies with the aggregate price and how it matters for firms' attention and price dispersion.

Monopolistic competitive intermediate firms produce with a linear production technology: $y_{it} = \theta_{it}n_{i,t}$. The final good is produced from a continuum of intermediate goods:

$$Y_t = \left[\int_0^1 (y_{it})^{\frac{\varepsilon-1}{\varepsilon}} di \right]^{\frac{\varepsilon}{\varepsilon-1}}$$

We assume that wages are determined by a wage rule that captures wage rigidity:

$$w_t = \bar{w} \left(\frac{Y_t}{\bar{Y}} \right)^x$$

For simplicity, we assume an exogenous money supply $M_t = P_t Y_t$. Money supply (and nominal GDP) follows a random walk with drift m :

$$\Delta \ln M_t = m + u_t \tag{2.1}$$

where $u_t \sim N(0, \sigma_m^2)$, The payoff-relevant state for an individual firm is $z_{i,t} = (\theta_{it}, M_t)$. Following Flynn and Sastry (2022), we define the risk-adjusted profits as:

$$\Pi(z_i) = Y^{-\gamma} y_i \left(p_i - \frac{w}{\theta_i} \right)$$

where

$$y_i = Y \left(\frac{p_i}{P} \right)^{-\varepsilon}$$

The representative household's marginal utility is $Y^{-\gamma}$. Following Woodford (2003a), we interpret $\Pi(z_i)$ as the financial-market valuation of the firm's random profit stream. The firm's decision is to choose a stochastic choice rule $g(p|z_i)$, a mapping from states of the world to distributions of actions, such that its profit net of the cognitive cost is maximized. This is because firms do not

have perfect information on M_t due to cognitive constraints, We assume θ_{it} , the firm-level labor productivity, is fully observable. Therefore, the only uncertainty comes from the aggregate demand uncertainty.

There's an information cost $c(\cdot)$ of paying attention to aggregate conditions (thus making more precise decisions). Intuitively, a more precise posterior distribution requires a higher information cost. Generally, the following cost function could characterize the negative expected entropy of the action distribution multiplied by the scaling λ_i , capturing that it's costly for agents to avoid mistakes or misoptimization.

$$c(g, z_{i,t-1}|f, \lambda_i) = \lambda_i \int \int g(p|z_i) \log(g(p|z_i)) dp f(z_i|z_{i,t-1}) dz_i \quad (2.2)$$

Decisions are separable across time, so the firm's optimization problem can be written as:

$$\max_g \int \int \Pi(p, z_i) g(p|z_i) dp f(z_i|z_{i,t-1}) dz_i - c(g, z_{i,t-1}|f, \lambda_i) \quad (2.3)$$

In equilibrium, the following aggregation of individual prices should satisfy

$$P = \left(\int p_i^{1-\varepsilon} di \right)^{\frac{1}{1-\varepsilon}} \quad (2.4)$$

Model Solution. We solve the above problem using a linear quadratic approximation method. We define an intermediate firm's ex-post optimal price

$$p^*(z_i) = \arg \max_p \Pi(p, z_i)$$

Denote the risk adjusted profits at the optimal price level $(p^*(z_i), z_i)$ as $\bar{\Pi}(z_i)$. The aggregate of ex post optimal price is

$$P^* = \left(\int p^*(z_i)^{1-\varepsilon} di \right)^{\frac{1}{1-\varepsilon}}$$

In turn, we may make a second-order approximation of Π at the optimal price level:

$$\tilde{\Pi}(p, z_i) \approx \bar{\Pi}(z_i) + \frac{1}{2} \Pi_{pp}(z_i) (p - p^*(z_i))^2$$

An equilibrium is defined as a stochastic choice rule g and a transition density function f such that: (i) firms' choice rules g solve 2.3 given the transition function f ; (ii) the transition density f

is consistent with g together with the wage rule.

We can solve for the optimal stochastic choice rule:

$$p_i = p^*(z_i) + \sqrt{\frac{\lambda_i}{\underbrace{|\pi_{pp}(z_i)|Y^{-\gamma}}_{\text{misoptimization}}}\nu_i} \quad (2.5)$$

where ν_i is an idiosyncratic i.i.d. Gaussian shock, which captures firms' mistakes in pricing. 2.5 is derived by taking the first-order condition of 2.3 with respect to g . The nice closed-form solution results from the entropy cost function assumed in 2.2.

The misoptimization term, denoted by $m_i = \mathbb{E}((p_i - p^*(z_i))^2|z_i)$ is simply the mean-squared-error objective function in many inattention models. It captures both the extent of misoptimization and the level of attention. Aggregate attention A is the average cognitive cost (entropy) across i . Average misoptimization M is then the average m_i .

Theorem 1. *Under parameter restriction $1 + \gamma - \varepsilon > 0$,*

1. *aggregate attention A is increasing in the aggregate inflation P_t/P_{t-1}*
2. *aggregate misoptimization M (also the dispersion of prices) is decreasing in the aggregate inflation P_t/P_{t-1}*

Since the exercise is static, we interpret this result as follows. Given the previous period's price, if inflation rises which leads to a higher aggregate price today, the dispersion of prices becomes smaller. This model predicts a different relationship between inflation and price dispersion, at the core of which is the state-dependent attention to aggregate state—as inflation surges, the cost of misoptimizing also become larger; this endogenously leads to more attention paid on inflation which in turn leads to lower price dispersion.

3 Background and Data

3.1 Background: The 1940s China

In the 1940s, China underwent two wars, the War of Resistance Against Japan (1937–1945, part of the Second World War) and the Chinese Civil War (1946–1949, hereafter referred to as the Civil War). This period also witnessed unprecedented hyperinflation. This section briefly out-

lines how hyperinflation developed during these wars, the government’s policy responses, and their implications for our study.

The hyperinflation began in 1939 as Japanese troops gradually occupied territories in the east, leading to massive migration to the west. The increased population and higher wages, driven by extensive infrastructure spending in western cities, initially caused grain and cotton yarn prices to rise, which spread to other goods’ prices. The higher cost of living led to higher nominal wages, creating a wage-price spiral (Chang, 1958). The sharp drop in government revenues, wartime supply shortages, and excessive money creation by the central bank have further contributed to increased general price levels.

China’s victory in World War II in August 1945 boosted confidence in postwar economic recovery prospects. In the following months, grain prices dropped substantially for the first time in years. However, the outbreak of the Civil War caused prices to soar again. Hyperinflation worsened due to unfettered military expenses financed by money issuance. According to the Central Bank of the Republic of China, the general price level in Chungking City rose by over 30 million times from January 1946 to April 1949.

The government attempted to monitor and suppress hyperinflation throughout the 1940s, but these efforts were rarely effective. In May 1941, recognizing the importance of food during wartime, the government established the Ministry of Food to collect grain market information every day or every two days 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 only implemented in a few leading cities referred to as “special municipalities,” such as Nanking, Shanghai, and Chungking, and were short-lived due to ineffective governance (see Chang, 1958). Details on these price regulation policies are relegated to Appendix B.2.

On August 19, 1948, the Nationalist government swiftly implemented a currency reform fearing further economic collapse. A new currency, *Gold Yuan Certificate*, replaced the old currency, *Fabi*, at a rate of one to three million. Unfortunately, this currency reform also failed quickly, effectively acting as a mere exchange of coins and causing prices to rise even faster. The monetary system eventually collapsed, and the government went bankrupt in credit at the beginning of 1949.

Implication for our study. Conventional studies of price setting primarily focus on low-inflation episodes partially because hyperinflation is uncommon and, when it happens, usually doesn’t last long. In addition, micro-level price data were not easily accessible during these events. In the

sample we studied, inflation was persistently high for as long as eight years; government regulation on prices was temporary and ineffective; and the local government officials kept a close record of price information at a very high frequency (at least every two days). These features provide a unique and valuable laboratory to study price adjustment in an environment with persistently high inflation.

3.2 Data Construction

We collect and digitize thousands of historical files by hand and compile three primary data sets: city-level grain prices, information on battles, and the newspaper coverage of prices. We now describe our data sets and direct readers to Appendix C for more details.

City-Level Prices. The city-level price data set consists of wholesale grain prices across 314 cities in 28 provinces in China from 1941 to 1948. We manually digitize the grain prices from three internal periodicals published by the Ministry of Food, which document how local government officials collected grain prices. In each city, one representative was sent to rice or wheat wholesale market and reported only one transaction price that was representative to that city to the Ministry of Food via telegraph.

All prices were denominated in Fabi yuan for every 50 kilograms² of grain before the currency reform on August 19, 1948. After that, the denomination changed the currency to Gold Yuan. We exchange all prices after the currency reform into Fabi using an exchange rate of 1/3,000,000.

Due to the lack of capacity in certain regions, the Ministry of Food did not collect grain price information for all 314 cities in all periods. Also not included in our sample are the data for areas not controlled by the Nationalist government, that is, the Communist Party-controlled and Japanese-occupied cities. Data availability varied over time as the state capacity and war situation evolved. The first periodical reports daily rice (wheat) prices from April 1 (April 30), 1941, to December 25, 1942. It initially only covered Chungking City and cities in Sichuan province and gradually expanded to cities in the entire Nationalist government-controlled areas around April 1942. The second periodical covers daily grain prices from December 19, 1942 to June 30, 1944. The third source records prices every two days from July 2, 1944, to November 30, 1948. Please see Section C.1 and Figure C.4 in the appendix for data availability details.

²In original archives, the unit was *shidan* (in Chinese, 市石/市担)=100 *shijin* (in Chinese, 市斤) which equals to 50 kg.

For empirical purposes, we take weekly averages of grain prices to unify data frequencies over different periods and to eliminate within-week price noises in each city. To mitigate the potential impact of unbalanced panel, we conduct baseline empirical analysis for subsamples of different periods and exclude cities with too many missing observations for robustness checks.

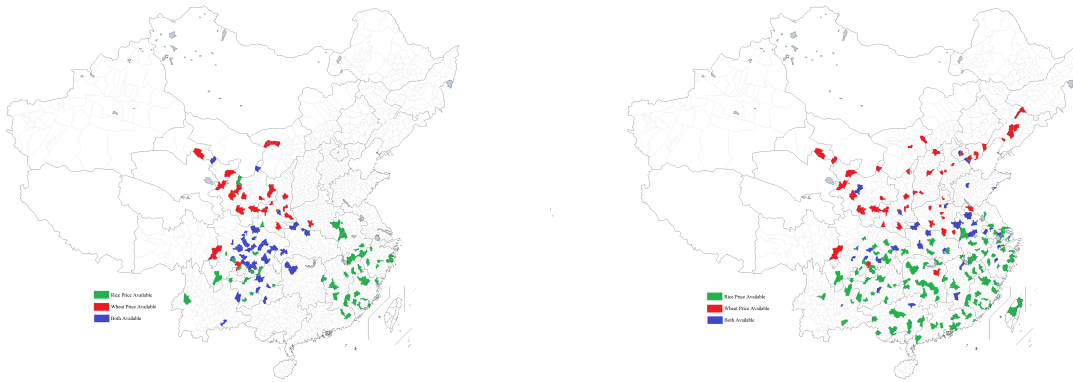
Figure 1 plots the geographical distribution of prices using snapshots of the raw data in November 1944 and November 1946. There are three observations from these plots. First, our sample covers fewer cities before 1945, when WWII was over, due to inaccessible data in Japanese-occupied regions. Second, our rice data mainly come from the south, and wheat data are primarily from the north, apparently driven by the difference in dietary habits in the southern and northern parts of China—people in the south primarily consume rice products, and those in the north primarily consume food made from wheat. Third, there’s substantial price variation across regions, illustrated by Panels (b) and (c). Our primary focus in this paper is understanding how this geographical distribution of prices varies over time. To validate our use of the grain prices as proxies for the overall price level in each city, we collect the daily wholesale price indices from the Central Bank’s internal periodical, the *Finacial Weekly*. Data are available from November 1945 to April 1949, but only in four leading cities: Shanghai, Chungking, Canton, and Kunming. In the 1940s, China was an underdeveloped country with agricultural output constituting a large share of its GDP. The wholesale price index is calculated by the weighted average prices of 23 goods categories. The index assigns weights of 38.6% and 13.7% to rice and wheat prices, respectively. Therefore, although we do not have the overall price index for all the cities, the rice and wheat prices used in this paper should represent the general price level well.

Figure 2 plots the year-over-year changes in rice, wheat, and wholesale prices for Shanghai and Chungking, two cities where wholesale price indices are available. Not surprisingly, the trends of rice and wheat prices resemble the wholesale price as they take the most weight in constructing the overall price index. In addition, the annual inflation rates were extraordinarily high over our sample period and kept climbing.

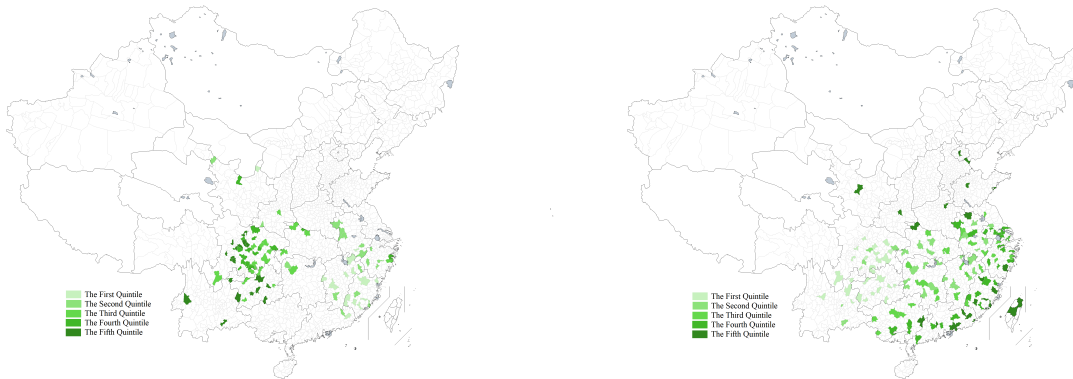
Nationwide Prices. Since the nationwide price indices of high frequency in the 1940s are not directly available, we construct them by calculating the arithmetic average of cross-city grain prices or the average prices weighted by each city’s population in 1947. The nationwide inflation rate is then calculated as the log change in this national price. In our baseline exercise, we adopt the population-weighted average grain prices across cities in calculating nationwide inflation rates

Figure 1: Geographical Distribution of Prices

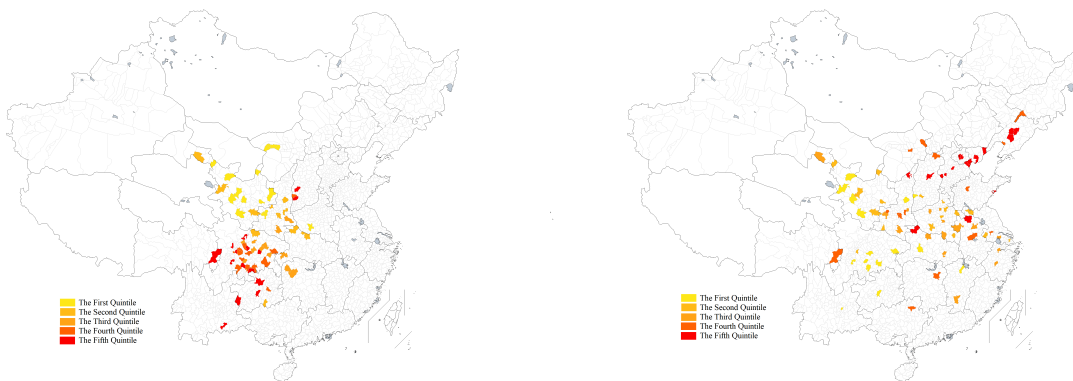
(a) Available Data on Rice and Wheat Prices



(b) Distribution of Rice Prices



(c) Distribution of Wheat Prices



Notes: These figures present the sample coverage in (a) and the geographical distribution of rice and wheat prices in (b) and (c) in November 1944 (left) and November 1946 (right), which present as two representative samples during WWII and the Civil War.

unless otherwise noted.

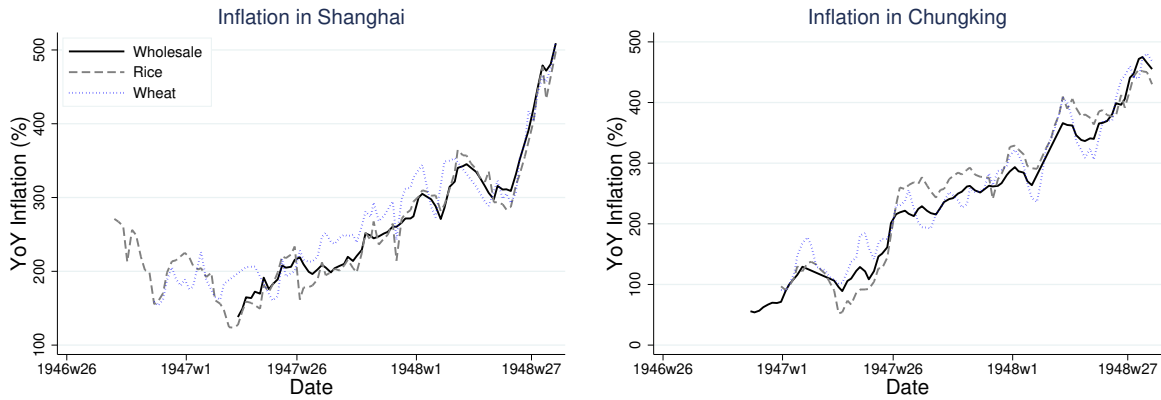
Battlefields. We compile a data set of spatiotemporal information on 145 major battles during the two wars from April 1941 to November 1948. We document each battle’s duration (beginning and ending dates) and the location of its core battleground. We then construct a war exposure indicator $war_{i,t}$ for each city i at each time t . Specifically, $war_{i,t} = 1$ if there was a major battle within k kilometers of the city i at time t . In our baseline exercise, we adopt $k = 50$ kilometers to calculate this war variable.

In total, there were thousands of combats or conflicts in our sample period, but we only consider major battles because they were more likely to increase market frictions more significantly. We also do not investigate military actions directly targeting any specific city because a city’s grain price was mostly unavailable if attacked. Instead, we examine how price dispersion was affected if sampled cities were exposed to their nearby battles.

Newspaper Coverage of Inflation. We review articles that covered inflation or prices in three of the most well-known newspapers at that time, *Shun Pao*, *Ta Kung Pao*, and *Sin Wan Pao*³ to explore how public’s attention to inflation varied over time. For each newspaper issued daily in the 1940s, we measure public “attention to inflation” by counting the articles with the following words in its headlines, charts, or main texts: “general price levels (物价, in Chinese),” “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).”

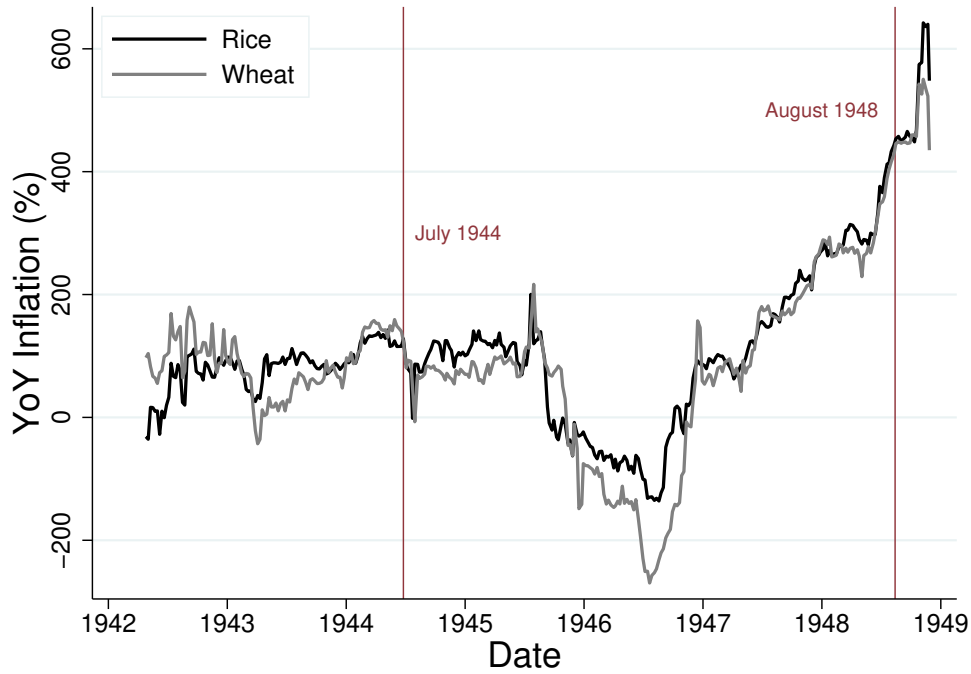
³In Chinese, 申报, 大公报, and 新闻报, respectively.

Figure 2: City-Level Inflation



Notes: These figures present the weekly year-over-year inflation rates from the end of 1946 towards 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: The figure presents the weekly year-over-year nationwide inflation rates measured using rice or wheat price data.

3.3 Descriptive Statistics

Table 1 summarizes the grain price-based inflation statistics. We use our weekly grain prices for each city to calculate its week-over-week and year-over-year inflation rates each week. We find very similar statistics for rice and wheat inflation. On average, a city’s price level increased by 3%-4% in a week or around 180% in a year. We then use population-weighted average grain prices across cities to generate nationwide inflation sequences. In a similar magnitude with city-level average inflation, aggregate price level soared at a weekly rate of 2.6% or a yearly rate of around 100% from 1941 to 1948.

Table 1: Summary Statistics

	Mean	Median	Max	Min	Standard Deviation	Number of Observations
<i>City-Level Inflation (%)</i>						
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
<i>Nationwide Inflation (%)</i>						
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
<i>Price Dispersion</i>						
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 Evidence

We study the empirical relationship between price dispersion and inflation from two perspectives. First, we investigate the time-series relationship between nationwide price dispersion and inflation. Second, to fully use the rich information embedded in our panel, we focus on the convergence of prices across cities as indirect evidence of how inflation affects price dispersion.

4.1 Time Series Evidence

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

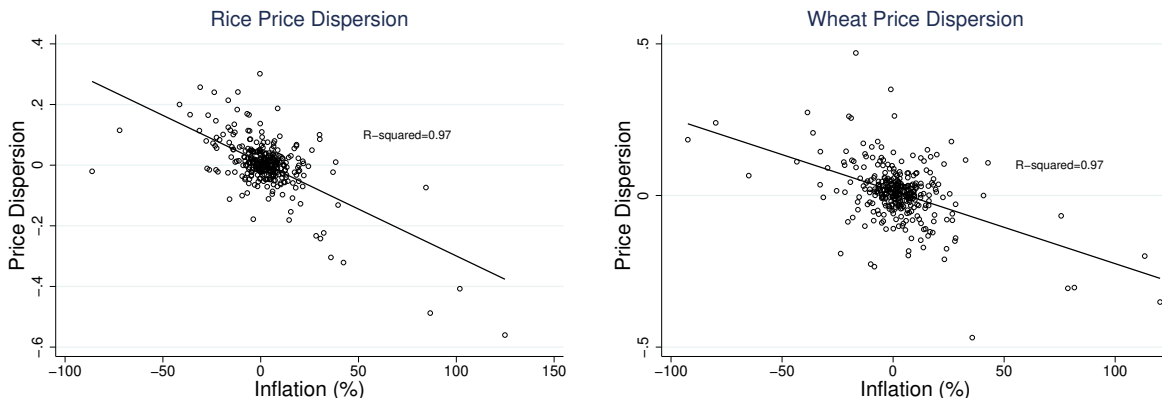
Figure 4 plots $\sigma_t - \beta_\sigma \sigma_{t-1}$ against π_t , the slope of which represents the OLS estimates of β . While many week-over-week inflation centers around 0, a significant number of price changes can be very high—in certain extreme weeks, the aggregate price can double over a week. Using this variation in inflation across time, we find a strong negative correlation between price dispersion and inflation—higher inflation is associated with substantially lower price dispersion. Moreover, the R-squared of this simple regression is very high, suggesting inflation and past dispersion can explain almost all of the variation in dispersion today.

While the method is very simple, this result stands in striking contrast with the theoretical prediction from classical models as we discussed in Section 2.1 and with the empirical findings from relatively low inflation episodes (e.g., Nakamura et al., 2018; Sheremirov, 2020). It suggests that some other channel can become relevant as inflation moves from moderate to very high, which we explore in more detail in Section 4.4.

4.2 Cross-City Evidence

Figure 4 presents a straightforward relationship between price dispersion and inflation. However, the aggregation of micro-level prices in calculating the standard deviation of prices has ignored a rich set of information at the micro level that could be important in shaping price and price dispersion dynamics. One such factor is wars, which increased trade and information frictions

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



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

across cities that have implications for the dispersion of prices. As noted in Section 3.1, wars took place throughout our sample period with substantial geographical variation; therefore, it's challenging to construct an aggregate war measure to better identify the role of inflation.

To fully leverage the micro-level features of our data, we explore how price convergence differs as inflation varies as an indirect test of the relationship between price dispersion and inflation. Our baseline specification of city-level price convergence is specified as follows:

$$\hat{p}_{i,t} = \alpha + \beta_{-1} \hat{p}_{i,t-1} + \beta_\pi (\hat{p}_{i,t-1} \times \pi_t) + \beta_{war} (\hat{p}_{i,t-1} \times war_{i,t}) + \beta'_x \mathbf{X}_i \times \hat{p}_{i,t-1} + \gamma_t + \theta_i + \varepsilon_{i,t} \quad (4.6)$$

where $\hat{p}_{i,t} := p_{i,t} - \bar{p}_t$ 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 fairly similar, close to that of a wholesale index in the years that these three prices coexisted. How aggregate inflation is constructed is unlikely to matter for the estimation results. Besides inflation, we also 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 at time t within 50 kilometers of the city i . In a robustness test, we show that our results are robust to different definitions of this variable. Time-invariant city characteristics \mathbf{X}_i including coastal access, railway access, terrain ruggedness, river density, soil suitability for rice or wheat, and the existence of treaty ports are defined and constructed in similar ways as in Gao and Lei (2021).

Details on these variables are relegated to Appendix C.3. To account for time or city-specific factors driving local prices, we include week and city-level fixed effects in all exercises.

This specification is similar to the literature on 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 $0 < \beta_{-1} < 1$. The larger β_{-1} is, the slower the convergence is. Besides, the collection of coefficients $(\beta_{\pi}, \beta_{war}, \beta')$ captures the impact of various factors on the speed of convergence. For example, the effects of inflation on price convergence are reflected in β_{π} —a positive β_{π} implies that higher inflation inhibits 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 to the national average faster as inflation rises (that is, when $\beta_{war} < 0$), then we should expect a negative correlation between price dispersion and inflation, conditional on past price dispersion. The linkage between convergence and dispersion can be (loosely) seen by taking a cross-sectional variance operator on both sides of Equation (4.6): a negative β_{π} is associated with the negative impact of π_t on the variance of $p_{i,t}$.

Table 2 presents the baseline estimates of the key coefficients in Equation 4.6 across various sample periods, using rice and wheat price data separately. Three concerns of our datasets determine our selection of different sample periods: fewer missing data since April 1942, a switch in the source and frequency of data in July 1944, and the currency reform in August 1948. Parameter β_{-1} is estimated to be between 0.9 and 1, indicating an unconditional process of price convergence on average. However, the actual convergence rate depends on the factors mentioned above and their associated parameters. The parameter of primary interest is β_{π} , the sign of which determines how the aggregate inflation affects price convergence. The primary conclusion we draw from this table is that β_{π} is consistently estimated to be significantly negative across samples, implying that as inflation rises, city-level prices converge faster to the aggregate—higher inflation is associated with a lower price dispersion conditional on past dispersion. Moreover, its estimates are similar in magnitudes between -0.0009 and -0.0019 . To put these numbers into perspective: take the estimates in column (4), ceteris paribus, a one-standard-deviation increase in week-over-week aggregate inflation would lead to 3.8 percent lower dispersion of log rice prices across the cities.⁴

β_{war} is estimated to be always positive across different samples and, most of the time, also

⁴As the standard deviation of nationwide weekly rice inflation is 18.5, together with the estimates in Table 2 column (4), the percent change in price dispersion due to a one standard deviation increase in nationwide inflation is: $-0.0019 \times 18.5/0.9171 = -3.8\%$.

Table 2: Price Convergence and Inflation in Subsamples

	<i>Rice</i>				<i>Wheat</i>			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_{-1}	0.9209*** (0.0080)	0.9181*** (0.0084)	0.9174*** (0.0090)	0.9171*** (0.0082)	0.9195*** (0.0106)	0.9162*** (0.0093)	0.9142*** (0.0108)	0.9083*** (0.0073)
β_{π}	-0.0015*** (0.0002)	-0.0016*** (0.0002)	-0.0015*** (0.0002)	-0.0019*** (0.0002)	-0.0010*** (0.0002)	-0.0010*** (0.0002)	-0.0009*** (0.0002)	-0.0012*** (0.0002)
β_{war}	0.0153 (0.0090)	0.0162* (0.0091)	0.0187* (0.0094)	0.0103 (0.0189)	0.0225* (0.0113)	0.0231** (0.0111)	0.0246** (0.0112)	0.0237 (0.0145)
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
Constant	0.0211*** (0.0021)	0.0205*** (0.0023)	0.0255*** (0.0035)	0.0217*** (0.0023)	0.0210*** (0.0022)	0.0199*** (0.0021)	0.0308*** (0.0043)	0.0204*** (0.0018)
N	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 (4.6) 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 $\hat{p}_{i,t-1}$ 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.

significant. This result suggests that wars in or surrounding a city would significantly hinder price convergence across cities. This is not surprising, given that wars are likely to cause disruptions to physical goods trade across cities and to information and communication infrastructure, 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 strong. Nonetheless, to mitigate concerns over this classic identification issue in linear dynamic panel models, we apply the difference GMM estimator proposed in [Arellano and Bond \(1991\)](#) and the system GMM estimator proposed in [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. This estimator is consistent, unlike the within estimator, however, it can suffer from weak instruments. The Blundell-Bond estimator in a system GMM estimation reduces the weak instrument problem and improves performance in

Table 3: GMM Estimation

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

Notes: This table reports the estimates of main coefficients of equation (4.6) 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.

finite samples. For both estimators, we limit the number of lags used as instruments to minimize the many-instrument problem.

Table 3 reports these results with our preferred sample period April 1942–August 1948. While the unconditional convergence coefficient β_{-1} can be sensitive to alternative estimators, the primary coefficient of interest, β_{π} , is estimated to be very similar to the within estimates shown in columns (4) and (8) of Table 2. In the case of wheat, the GMM estimates tend to be larger in magnitudes relative to the within estimate, suggesting an even stronger negative impact of inflation on the dispersion of prices across cities. In addition, we report the p-values of tests for serial correlation in the first-differenced residuals of Equation (4.6) against the null of no serial correlation. We show that AR(2) can be rejected using rice data and that AR(5) can be rejected using wheat, which motivates the use of the third and higher lags of the dependent variable as instruments for the former and the sixth and higher for the latter.

Robustness Check. To further check the validity of our baseline result across alternative definitions of variables and econometric specifications, we conduct a number of robustness tests, the results of which are related to Appendix D.1. In Table D.2, we combine results of three alternative specifications of the baseline estimation: (i) we use the simple arithmetic average of city-level grain prices in calculating nationwide inflation rates; (ii) we include fixed effects and cluster the standard errors at different levels than is specified in the baseline; (iii) we exclude cities with more than 80%

Table 4: Price Convergence under Low Inflation

	High-Quality Rice	Medium-Quality Rice	Low-Quality Rice
$\hat{p}_{i,t-1}$	0.9912*** (0.0111)	0.9956*** (0.0111)	0.9987*** (0.0168)
$\hat{p}_{i,t-1} \times \pi_t$	0.0068*** (0.0008)	0.0071*** (0.0012)	0.0074*** (0.0018)
N	46498	46498	40931

Notes: This table reports the estimates of main coefficients in equation (4.6) 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. 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. Both prefecture and month fixed effects are included.

missing observations over the period of the estimation sample to deal with potential issues with unbalanced samples. We obtain similar results across these specifications.

We also consider the nonlinear impact of inflation on price convergence rates and add an inflation-squared term as an additional regressor in the baseline equation. As displayed in Table D.3, though the first-order effect of inflation is partially absorbed by its second-order term, both are estimated to be significantly negative, which suggests that the impact of inflation on price convergence and price dispersion can be increasingly stronger in a high inflation regime than a lower one. We now turn to an external validity test for this argument.

4.3 Comparison Between High and Low Inflation Times

As the majority of our sample period was in high inflation, the conclusions drawn from the empirical exercise in previous sections are specific to a high inflationary environment. 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 they can be very different when aggregate inflation is low. To arrive at this argument, we use a readily available rice price dataset studied by Gao and Lei (2021) that features a different time period, 1870–1904, with low inflation throughout. We replicate our price convergence exercise using this data but with a few differences. First, this dataset has more detailed prices for different categories of rice, i.e., high, medium, and low-quality rice. We investigate them separately. Second, this sample period does not feature widespread wars, so we omitted the war variable. Third, the sample frequency is monthly compared with weekly in our baseline. Except for these differences, we follow the baseline exercise by including prefecture-level control variables and fixed effects.

Similar to the high inflation environment, we also find unconditional convergence of prices across prefectures, but at a much lower rate, as shown by the close-to-one estimate of β_{-1} . In contrast with Table 2, the coefficient on the interaction term $\hat{p}_{i,t-1} \times \pi_t$ is estimated to be significantly positive under the low inflation environment, suggesting that as inflation goes up, price dispersion rises as well—a starkly different impact compared with the high inflation episode.

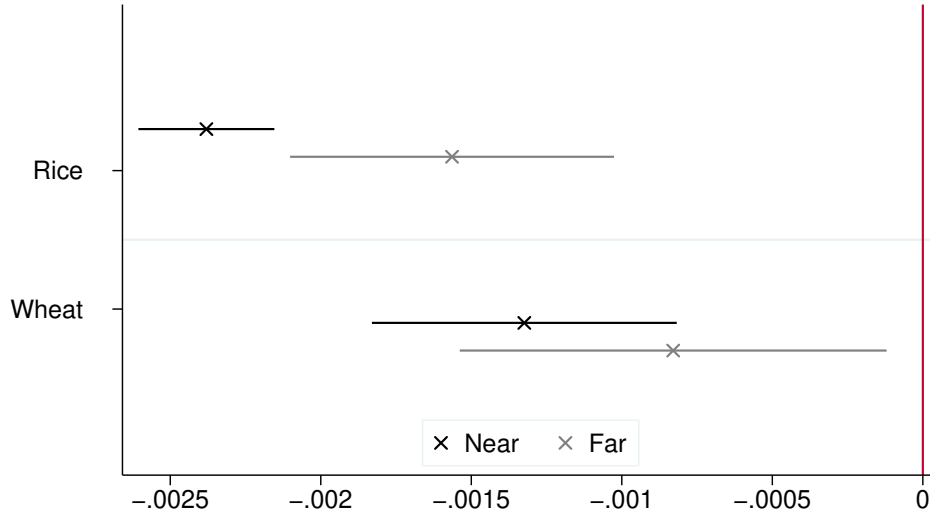
4.4 Inspecting the Mechanism

Information Channel. We have shown that in a high-inflation environment, prices across cities converge faster as inflation rises. Therefore, price dispersion decreases with inflation. In contrast, this relationship is the opposite when inflation is low. To further understand what might have caused these patterns, we investigate two groups of cities separately: those very close to and very far from big cities. In particular, we calculate the distance between each city and its nearest major city, one of the ten biggest cities at that time, and classify it in the "Near" or "Far" group if it lies in the bottom or top quarter of the distance distribution across all the cities.

Apart from the geographical distance, another feature that distinguishes these two groups is the ease of information acquisition or, relatedly, the extent of information friction. Big cities tend to be better informed of news due to more complete information infrastructure such as newspaper outlets, telegraph, radios, etc., while the remote ones are much less equipped with instruments that facilitate the transmission of information. Because of the rising cost of establishing such facilities with distance, the farther away from big cities, the worse the information friction problems. As such, testing for potential different convergence patterns across these two groups can potentially shed light on the importance of information frictions in explaining our baseline results.

Figure 5 plots β_π estimates together with their confidence bands for the "Near" and "Far" groups of cities. Two observations stand out. First, all of the coefficient estimates are significantly negative at the 90% level, suggesting that our baseline conclusion holds in the subsamples. Second, the impact of rising inflation on price convergence is more pronounced if the city is closer to a big city, which applies to both rice and wheat prices, albeit the coefficient difference across groups is not as statistically significant for wheat. Our interpretation of this result is that, consistent with the theory in Section 2.2, a higher cost of acquiring information for remote cities would impede price convergence and, therefore, lead to higher price dispersion.

Figure 5: Coefficient by Distance

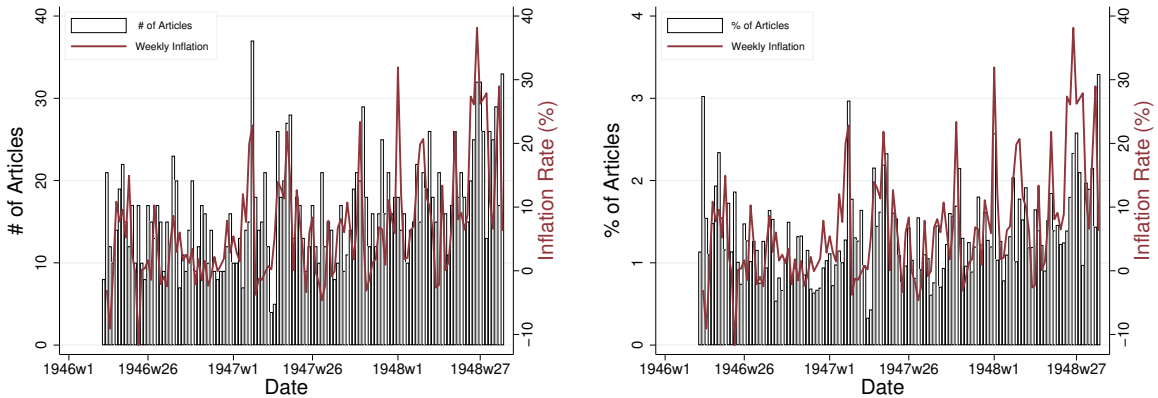


Notes: This figure plots the estimates of coefficient β_π for two subgroups defined by their distance to their nearest major city. "Near" refers to the cities at the bottom quarter of this distance distribution and "Far" refers to the top quarter. "x" s represent the point estimates and lines represent their 90% confidence intervals.

Suggestive Evidence on "Attention to Inflation". We've argued that information friction may play an essential role in explaining the impact of inflation on price dispersion across cities when inflation is very high. Our hypothesis for solving this puzzle is that at different levels of inflation, people pay different levels of attention; that is, attention to inflation depends on the level of inflation. This explanation echoes recent papers exploring factors that drive consumers' attention to inflation. For example, [Marcellino and Stevanovic \(2022\)](#), [Bracha and Tang \(2022\)](#), and [Korenok, Munro and Chen \(2022\)](#) find that the attention to inflation, measured differently across these papers, seems to rise with the level of inflation in the recent episode of high inflation.

We provide similar evidence using newspaper coverage of "prices" in our sample period as a proxy for the public's attention to inflation or the price level. It's especially relevant for these days when communication of important events and news was primarily conveyed via newspaper, radio, and telegraphs, among which newspapers reached a wider audience, and their contents could be relatively easily digitized. We digitize three major newspaper outlets in the 1940s by counting the appearance of article titles that are directly related to inflation or prices and use these data to construct measures of "attention to inflation" at the daily frequency, which is then aggregated to

Figure 6: Newspaper Articles on “Prices” in Shanghai



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 a Shanghai local newspaper *Sin Wan Pao*, measured by the number of news titles that include “price,” “rice price,” “grain price,” “price index,” “inflation,” “living index,” and “living expense index.” The graph on the left plots the total number of appearances of these titles, and the one on the right plots the fraction of these titles among all news articles.

the weekly frequency to be merged with our city-level inflation data.

We present in Figure 6 two of our attention measures coming from one of these three newspapers, *Sin Wan Po*—a Shanghai local outlet—against the weekly wholesale price inflation in Shanghai. The key observation is a strong comovement between inflation and the attention paid to the price information: at each peak of inflation, the number and fraction of articles on prices (broadly defined) surged dramatically. This positive correlation holds very well if we change the scope of keyword searches, use data from alternative newspapers, or investigate different cities. Additional results can be found in Appendix D.2.

5 Conclusion

This paper revisits the relationship between price dispersion and inflation when inflation is very high. Using a novel high-frequency city-level grain price data set in 1940s China, we provide robust evidence that in the high-inflation environment, price dispersion decreased with inflation, and relatedly, city-level grain prices converged faster to the national average as the inflation rate climbed up. Our finding goes against predictions of this relationship in standard monetary models. We illustrate our results in a pricing model with state-dependent “attention to inflation”: agents pay more attention to overall prices when inflation is higher, altering the relationship between price dispersion and inflation as inflation changes. We also find evidence for the strong comovement between newspaper coverage of prices and inflation itself, which corroborates our attention theory.

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Online Appendix

A Price Dispersion in Canonical Monetary Models

to be added

B Details on the Historical Background

B.1 The Timeline of Wars and Price Regulations

Our 1940s data sets cover part of WWII and the entire Civil War. We list the key events in these wars and the major price control policies in this hyperinflation era.

July 7, 1937	•	Marco Polo Bridge Incident: full-scale Japanese invasion of China started.
December 13, 1937	•	The fall of Nanking City.
October 1938	•	The fall of Canton City and Hankow City.
December 1938	•	Price Regulating Committee set up in Chungking city.
September 6, 1940	•	Chungking declared as wartime capital city.
November 1942	•	A new comprehensive program strengthening price controls adopted.
August 15, 1945	•	Japanese surrendered.
June 1946	•	The full-scale Civil War started.
February 16, 1947	•	Economic emergency measures announced: ceiling prices of daily necessities in a few big cities.
May 5, 1947	•	Fixed prices/price ceilings for rice and other necessities relinquished.
August 19, 1948	•	Currency Reform implemented: prices frozen.
October 1948	•	Price regulations abandoned.
September 1948–June 1949	•	Military and economic failures of the Nationalist government.

Table B.1: Timeline of Events on the Wars and Price Regulations

B.2 Price Regulation Policies and Their Failures

Chang (1958) describes several price regulatory policies during the hyperinflation era studied in our sample. These include a strengthened price control program at the end of 1942, economic emergency measures in 1947, and the well-known currency reform in 1948.

The November 1942 price regulation policies included price ceilings on daily necessities, rationing of consumer goods, government buying and selling of commodities, limitations on inventories and use of scarce goods, and wage ceilings. However, these direct and indirect controls on prices have had little impact on the rise of prices. First, the direct price ceiling policies were imposed on only a few commodities in some big cities. Their nationwide impacts were very limited. Second, the government's intervention in the market by buying, selling, and rationing consumer goods had some effect on wholesale prices but little on retail prices due to a lack of comprehensive and coordinated administrative machinery. Regarding rice prices, the government's purchases and sales of rice represented only a tiny percentage of the total free market supply without significantly impacting rice prices.

In February 1947, the government reimposed similar price control policies. Same as before, the impacts of these policies on prices were short-lived, lasting for a month or so before consumer goods prices surged again in April 1947. In the case of rice, fixed rice prices led to dealers suspending the rice markets, widespread starvation and social unrest, and eventually, the elimination of rice price ceilings in early May.

In August 1948, the government froze prices and wages, adopting a monetary reform by introducing a new currency called the Gold Yuan. In particular, the unit of value of this new currency was defined as 0.2217 centigram of pure gold. The new notes were exchanged at 1 to \$3,000,000 relative to the old currency Fabi. Together with strict law enforcement, prices kept stable in some cities like Shanghai for around six weeks. However, in most other cities where these policies were not executed strictly, the inflation problem became even worse. As a result, in late October, the price and wage ceiling systems became inoperative two months after their initial introduction.

While several attempts were made to regulate market prices during this hyperinflation era, almost none significantly and widely impacted consumer prices. Moreover, they were abolished quickly due to their unintended consequences on the market and society, making their impact even less pronounced.

C Details on the Data

C.1 Grain Prices

Data Collection. We manually digitized 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, Nationalist government. These periodicals are stored in microfilm or original paper format at the National Library of China. Although they had different journal titles, they were the same publication and were compiled in one consecutive numbering of issues.

From Issue 1 to Issue 89, the periodical *Grain Briefs* reported rice prices from April 1, 1941, to December 25, 1942, and wheat prices from April 30, 1941, to December 25, 1942. A typical archival sheet in this periodical, like Figure C.1, lists rice or wheat prices for a few cities on discrete dates.

From Issue 90 to Issue 168, the *Grain Weekly Report* covered daily grain prices from December 19, 1942, to June 30, 1944, with a representative archival sheet listing rice or wheat prices on seven consecutive dates within a week for 10 to 30 cities, as displayed in Figure C.2.

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 sheet in this periodical typically lists rice or wheat prices on five alternative dates within ten days for 20 to 40 cities, as shown in Figure C.3. Issues 1 to 133 were handwritten and mimeographed, while issues 134 to 328 were type printed.

The grain prices were only available for cities controlled by the Nationalist government from April 1941 to November 1948. They were denominated in the currency of Fabi and, after the currency reform on August 19, 1948, in the currency of Gold Yuan. We converted all prices after the reform into Fabi denomination using a replacement rate of 1/3,000,000.

Figure C.1: A Sample in *Grain Brief*

河南省各主要市場電報米麥價格表				
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	260.00	150.00	120.00	55.00
中等小麥	150.00	80.00	92.00	45.00

Notes: This sample sheet from the *Grain Brief* shows 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 of China on November 15, 1941 (30th year in the Annals of the Republic of China). These prices were denominated in Fabi yuan (國幣元, in Chinese) and reported via telegraph.

Figure C.2: A Sample in *Grain Weekly Report*

The image shows two tables from a grain weekly report. The top table is titled '陕西省各主要粮食市场米价统计表' (Shaanxi Province Major Grain Markets Rice Price Statistical Table) and the bottom table is '山西省各主要粮食市场米价统计表' (Shanxi Province Major Grain Markets Rice Price Statistical Table). Both tables show prices for various grain types (rice and wheat) across different markets in the respective provinces, with columns for dates from Monday to Sunday, current prices, previous week prices, and percentage changes.

Notes: The two tables on a sample sheet from the *Grain Weekly Report* display 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 of China, respectively, from May 1 to 7, 1943 (32nd year in the Annals of the Republic of China). 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.

Figure C.3: A Sample in *Grain Ten-Day Report*

The image shows a table titled '中国各重要粮食市场中等熟米价格统计表' (China's Major Grain Markets Medium-quality Rice Price Statistical Table) for the first ten days of the month. The table lists prices for various cities across different provinces, including Nanjing, Shanghai, Guangzhou, Chongqing, Tianjin, Qingdao, and others. Columns include the city name, prices for the 2nd, 4th, 6th, 8th, and 10th days, current average prices, previous average prices, and percentage changes.

Notes: This sample sheet from *Grain in Ten Days* displays wholesale prices of medium-quality rice for one *shidan* (市石, in Chinese, equivalent to 50kg) across many cities' grain markets in multiple provinces of China during the first ten days (上旬, in Chinese), i.e., from November 1 to 10, 1948 (37th year in the Annals of the Republic of China). These prices were denominated in *Gold Yuan Certificate* (金圆券, in Chinese) and reported every other day. The tables also report average prices for the current ten days (本旬) and the previous ten days (上旬), along with their percentage changes.

Data Availability. Although 314 cities had grain prices available (270 cities with rice prices and 239 cities with wheat prices) for at least one date from April 1941 to November 1948, the availability of price data varied over time due to changes in the Nationalist government's capacity and territories under its control during wartime. On average, approximately 101 cities reported rice

prices at least once weekly during the entire period, and around 60 cities reported wheat prices. These numbers increased to 107 and 63, respectively, after April 1942. Figure C.4 illustrates the number of cities with grain prices available by week.

The Ministry of Food of the Nationalist Government initially compiled the *Grain Brief* using the *Telegrams on Grain* data from the Sichuan province-Chungking city region, documenting rice and wheat prices for only about 60 and 30 cities, respectively. However, its reporting scope expanded dramatically from early to mid-1942 (with the publication of the 59th issue) to include almost every province controlled by the Nationalist government.

Starting from February 13, 1943, the *Grain Weekly Report* ceased reporting wheat prices in a few southern regions, significantly reducing the number of cities included in the report.

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, the 171st issue was a special edition summarizing the grain situation in the first half of 1944. Thus, grain prices for most areas in late July 1944 were not reported, except for some cities' prices recorded in the 172nd issue, resulting in the sharp declines shown in Figure C.4.

Due to the unfavorable situation in the Sino-Japanese War (Operation Ichi-Go, Battle of Henan-Hunan-Guangxi), reporting of rice prices in provinces such as Guangxi, Guangdong, Zhejiang, and Anhui was discontinued from September 1944 (the 175th issue) on.

However, after the victory in World War II in August 1945 (the 208th issue), documentation of rice prices gradually resumed and expanded to include areas previously occupied by Japan.

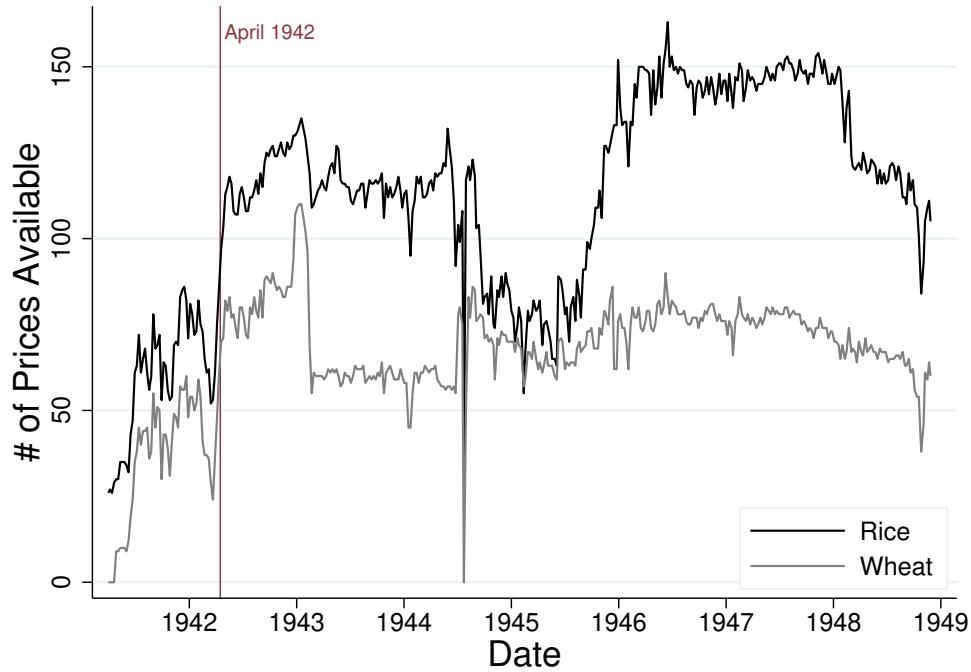
C.2 Information on Battles

We collect spatiotemporal information on 145 major battles. Forty major fighting during the War of Resistance from April 1, 1941, to August 17, 1945, are documented in *The Frontal Battlefield Operations in China's War of Resistance Against Japanese Aggression*. The other 105 battles during the Civil War from September 10, 1945, to November 30, 1948, are recorded in *The History of the Chinese People's Liberation Army (1945-1949)*. If a big battle is divided into different phases in the record, each phase counts as a battle separately.

We document each battle's duration (beginning and ending dates) and its core location. The center location of a battle is determined by the arithmetic or weighted⁵ average of the longitudes and latitudes of cities/counties mainly involved.

⁵For each battle, a city's weight is given by the word count of the city name in the battle record.

Figure C.4: Number of Observations Each Week



Notes: The figure presents the number of observed prices of rice and wheat each week.

C.3 City Characteristics

We collected city characteristics as control variables for tradeability, which might affect 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 variable definitions and their data sources are described below.

Coast Access is a dummy variable that takes a value of one for cities on the coast. *Railway Access* is a dummy variable that takes the value of one if a train station existed in a given city from 1941 to 1948. Data source: Zhang (1997). *Terrain Ruggedness* is calculated by taking the standard deviation of elevations within 20 kilometers of the location of the city government. Data source: USGS (2018) for elevation, Amap (AutoNavi) for the location (geographical coordinates) of the city governments. *River Density* is the density of the river network surrounding a city, measured by the length (the unit is decimal latitude and longitude) of navigable river channels within 20 kilometers of the location of the city government. Data source: Shen (N.d.). *Soil Suitability for Rice or Wheat* is calculated by taking the average value of the soil suitability measure within 20 kilometers of the location of the city government. Data source: Fischer et al. (2012). *Treaty Port*

is a dummy variable that takes the value of one if a city was either a treaty port or a subordinate jurisdiction of a treaty port. Data source: [Yan \(2016\)](#).

D Additional Empirical Results

D.1 Robustness Tests

Table D.2: Alternative Robustness Tests

	<i>Rice</i>			<i>Wheat</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
β_{-1}	0.9181*** (0.0091)	0.9836*** (0.0035)	0.9156*** (0.0084)	0.9105*** (0.0079)	0.9854*** (0.0029)	0.9211*** (0.0074)
β_{π}	-0.0022*** (0.0002)	-0.0019*** (0.0001)	-0.0019*** (0.0002)	-0.0017*** (0.0003)	-0.0012*** (0.0002)	-0.0014*** (0.0002)
β_{war}	0.0020 (0.0170)	0.0080 (0.0284)	0.0140 (0.0228)	0.0243 (0.0150)	0.0251* (0.0141)	0.0276* (0.0138)
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
Constant	0.0040** (0.0018)	0.0146*** (0.0017)	0.0213*** (0.0022)	0.0021 (0.0015)	0.0112*** (0.0022)	0.0174*** (0.0017)
N	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 (4.6) 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 (3), 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 (4), we include fixed effects at the province level and cluster the standard errors by city, whereas for the other columns we follow the baseline practice by including fixed effects at the city level and cluster the standard errors by province. In (3) and (6), we remove cities with more than 80% missing data from our estimation sample.

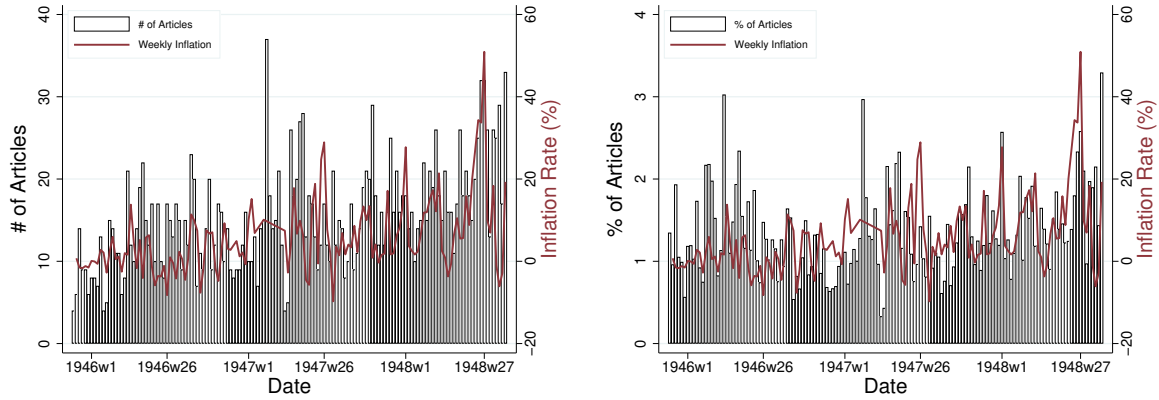
Table D.3: Nonlinear Effects of Inflation

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

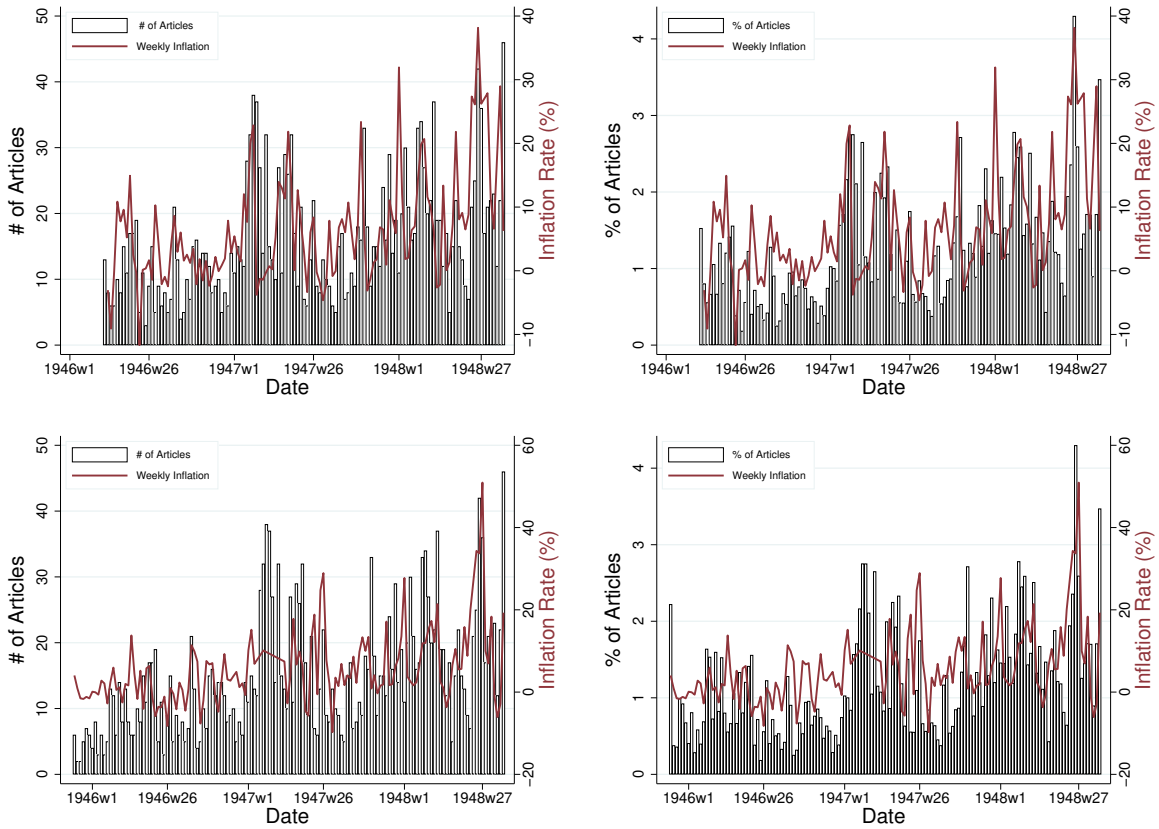
D.2 Newspaper Coverage

Figure D.5: Newspaper Articles on “Prices” in Chungking



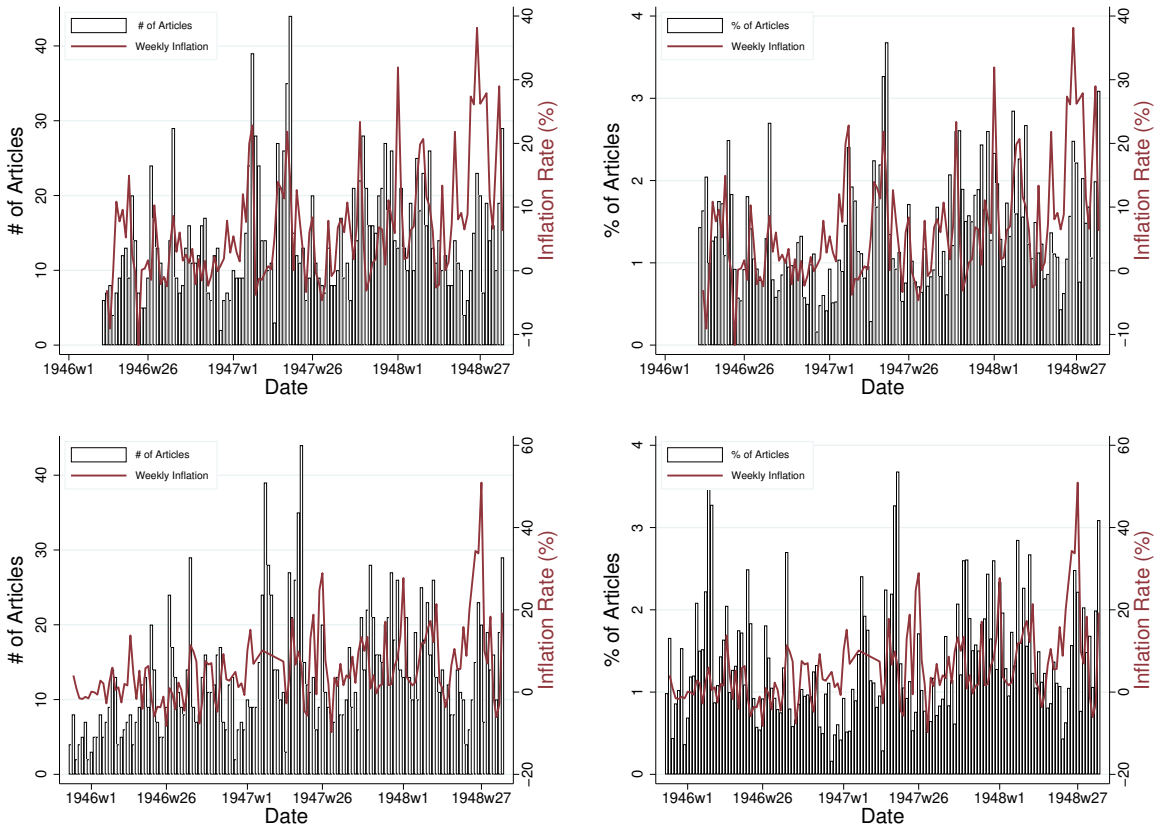
Notes: These figures plot the weekly inflation in Chungking, measured by the week-over-week change in the wholesale price index, against the coverage of prices in the newspaper outlet *Sin Wan Pao*, measured by the number of news titles/headlines that include “price,” “rice price,” “grain price,” “price index,” “inflation,” “living index,” and “living expense index.” The graph on the left plots the total number of appearances of these titles, and the one on the right plots the fraction of these titles among all news articles.

Figure D.6: Newspaper Articles on “Prices” in Shun Pao



Notes: These figures plot the weekly inflation in Shanghai (first row) and Chungking (second row), measured by the week-over-week change in wholesale prices, against the coverage of prices in the newspaper outlet *Shun Pao*, measured by the number of news titles that include “price,” “rice price,” “grain price,” “price index,” “inflation,” “living index,” and “living expense index.” The graphs on the left plot the total number of appearances of these titles, and the ones on the right plot the fraction of these titles among all news articles.

Figure D.7: Newspaper Articles on “Prices” in Ta Kung Pao



Notes: These figures plot the weekly inflation in Shanghai (first row) and Chungking (second row), measured by the week-over-week change in wholesale prices, against the coverage of prices in the newspaper outlet *Ta Kung Pao*, measured by the number of news titles that include “price,” “rice price,” “grain price,” “price index,” “inflation,” “living index,” and “living expense index.” The graphs on the left plot the total number of appearances of these titles, and the ones on the right plot the fraction of these titles among all news articles.

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