# Price Setting Dynamics in High Inflation: Evidence from Turkish Grocery Retailers[*]

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**Abstract**

We study price-setting dynamics in the Turkish grocery retail sector during high inflation using a novel daily micro-level dataset of 48.8 million observations from 2020–2024. We document three key patterns. First, price adjustments are asymmetric: they respond almost one-for-one to negative competitor-price gaps, but remain minimal for non-extreme positive gaps. Second, the state-dependent hazard function is asymmetrically V-shaped, with adjustment probabilities high for negative gaps, but marginally rising for positive gaps. Third, inflation expectations distort the magnitude of adjustment, shifting the kink of the size function rightward by 14.7%. We calibrate a state-dependent pricing model with trend inflation to match these moments, replicating the observed asymmetry while producing inflation dynamics consistent with empirical results.

**JEL codes:** E31, E32, E37, E52, D84

**Keywords:** monetary non-neutrality; state-dependent pricing; price-gap proxy; macroeconomic asymmetries; inflation expectations; trend inflation.

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## 1 Introduction

The decision of firms to adjust prices in response to monetary shocks remains a central question in the macroeconomic literature. The state-dependent menu cost model of Golosov and Lucas Jr (2007) challenged the long standing time-dependent price adjustment mechanism of Calvo (1983), arguing that price adjustment decisions of firms are micro-founded as firms internalize the cost of changing prices. Karadi et al. (2024) propose an alternative specification within a linear-hazard, state-dependent pricing model, where firms adjust prices in response to misalignment with competitors, but do not systematically target the prices most sensitive to monetary shocks. In this paper, we show that under high inflation the symmetry and linearity argued in the standard state-dependent pricing models break down, and have more pronounced asymmetries and non-linear adjustment patterns. The Turkish economy presents a compelling case for studying this price-setting behavior under high inflation. Since 2020, Turkey experienced persistently annual high inflation ranging from 12.15% to over 85.51%, driven by exchange rate volatility and monetary policy uncertainty. In this inflationary environment, firms face heightened pressure to adjust prices frequently, yet the nature of these adjustments has important implications for inflation persistence and price distortions. We examine these pricing dynamics using unique daily price level data from Turkish grocery retailers during this period.

Our empirical findings reveal three key results about price-setting in high inflation environments. First, the magnitude of price adjustments exhibits strong asymmetry: firms adjust prices nearly one-for-one when their prices fall below competitors, but make minimal adjustments when priced above competitors. This asymmetry suggests that in high inflation settings, firms are more concerned with reducing their competitor-price gap rather than maintaining symmetric alignment around optimal prices. Second, the state-dependent hazard function also follows an asymmetric V-shaped pattern. When prices are below competitors, the adjustment probability remains high (around 25-35%) and largely invariant to the gap size, declining exponentially as the competitor-price gap approaches zero. For positive gaps, the hazard increases approximately linearly, but with a negligible slope 0.001, indicating that firms are less likely to reduce prices even when their price is above their competitors. Third, we document that informational distortions in firms' inflation expectations have an important role in shaping adjustment behavior, with the kink point in the adjustment size function shifting rightward from zero by approximately 14.7%, reflecting anticipatory price increases even when competitively aligned. These asymmetries challenge the canonical state-dependent pricing models, which typically assume symmetric adjustment probabilities around zero gaps (Golosov and Lucas Jr 2007, Karadi et al. 2024). While these models perform well in low inflation contexts, our findings suggest that high inflation alters firms' incentives. During periods of high monthly inflation, the cost of not adjusting prices when there is a negative price-gap is higher, and firms are more likely to adjust their prices so they mirror their competitors. However, firms have less of an incentive to reduce prices to close a positive gap as future inflation will likely push prices higher again.

To rationalize these empirical patterns, we develop a state-dependent pricing model that extends the framework of Karadi et al. (2024) to incorporate features specific to high inflation environments. Our model details an asymmetric piecewise adjustment function that captures the differential response to positive versus negative price-gaps, a modified hazard function with exponential decay for negative gaps and linear increase for positive gaps, and heterogeneous inflation expectations that shift firms' adjustment thresholds. We then calibrate the model to match our empirical moments, and simulate month-to-month inflation based on our parameter estimates. The model successfully reproduces both the level and volatility of observed inflation, generating month-to-month inflation rates between 1% and 15% that closely track the reported Turkish inflation rates.

### 1.1 Related Literature

This study adds to the body of research that leverages minimally parameterized models to assess the intensity of price selection in micro price data (Caballero and Engel 2007). Similar to Gagnon et al. (2013), Campbell and Eden (2014), and Karadi et al. (2024), we use the competitor-price gap as a proxy for the deviation from optimal price levels used in the various theoretical macroeconomics models. However, in contrast to these studies, we find that the probability of a price change is asymmetric relative to the price-gap. It increases with the magnitude of the competitor-price gap only when the gap is negative. For non-extreme positive gaps, this relationship is absent. Consistent with Eichenbaum et al. (2011), Carlsson (2017), and Karadi et al. (2024), we observe linear segments in the hazard function. However, unlike these studies, linearity does not hold across all states in our data, particularly when the competitor-price gap is negative. The nature of our hazard function complements the result of Luo and Villar (2021), who also documents an asymmetric hazard function, where the probability of price increases exceeds that of decreases. Similarly, in Mexico during high inflation periods, few price reductions are observed and both the frequency and average magnitude are the primary determinants of inflation (Gagnon 2009). On the other hand, Alvarez et al. (2019) examine firm level price adjustment behavior during episodes of hyperinflation and find that the frequency and size of price increases and decreases are symmetric around zero inflation. This contrast suggests that the asymmetry we observe may be a feature of high inflation environments, rather than hyperinflationary contexts.

We also contribute to the literature examining the magnitude of price changes in inflationary contexts. Nakamura, Steinsson, et al. (2018) find no evidence that price changes become larger as prices drift further from their optimal level under high inflation. Similarly, several other studies (Konieczny and Skrzypacz 2005; Kryvtsov and Vincent 2021; Dedola et al. 2021 and Karadi et al. 2024) find a symmetric relationship between competitor-price gaps and the magnitude of adjustments by firms. By contrast, our results align more closely with

Peltzman (2000), who document asymmetric price adjustment in response to macroeconomic shocks, with firms exhibiting a greater probability of price increases than decreases. Benzarti et al. (2020) in the context of value-added taxes (VAT) find that prices respond more to VAT increases rather than to decreases. Consistent with our results, this suggests that in certain contexts, firms may exhibit price selection behavior.

Finally, we contribute to the literature examining the role of distortion in information on inflation expectations in shaping firms' price-setting behavior. Drenik and Perez (2020) show that informational frictions are associated with greater price dispersion. Woodford (2009) demonstrate that when firms have imperfect information about current market conditions, they optimally review prices less frequently than under full information. Using survey data, Candia et al. (2024) find that U.S. managers during high inflation periods are largely uninformed about inflation trends and monetary policy, contributing to widespread inattention. By contrast, Coibion et al. (2020) show in a survey of Italian firms that inflation expectations causally affect prices, but the effect is small, short-lived, and does not cause systematic distortions in the frequency of price changes. Our findings, however, are consistent with evidence that distortions in inflation expectations can influence both the size and frequency of price adjustments.

The remainder of the paper is organized as follows. In Section 2, we present a theoretical framework for the firm's state-dependent hazard function and price adjustment function. Section 3 describes the data and the V-shaped sales-filtering methodology. Section 4 details the empirical methodology and reports the results for the hazard function and the adjustment-size function. Section 5 explains the calibration of the theoretical model to empirical moments and presents a Markov inflation simulation based on the calibrated parameters.

## 2 Model

Our theoretical model extends that of Karadi et al. (2024) in a high inflation context. We define the key features of the model: optimal price versus posted price, the hazard function, and the density of gaps. The rest of the model is a standard quantitative dynamic stochastic general equilibrium price-setting model with random price-adjustment costs. For details and derivations see Costain and Nakov (2011).

In line with Karadi et al. (2024), we assume that there is a continuum of differentiated goods ($i$) sold in a market with monopolistic competition. Each firm sets its optimal price $p^*_{i,t}$ at time $t$, which is determined as the sum of aggregate ($m_t$) and idiosyncratic factors ($v_{i,t}$). In order to model trend inflation, let $m_t$ follow a random walk with a drift ($\mu$):

$$m_t = m_{t-1} + \mu + \epsilon_t \text{ where } \epsilon_t \sim N(0, \sigma_\epsilon) \tag{1}$$

This is the standard baseline specification from the trend inflation literature (Stock and Watson 2007; Mertens 2016; Chan et al. 2018; and Luo and Villar 2021).

An increase in $m_t$ shifts the optimal nominal price of all firms at time $t$ and $v_{i,t}$ are firm-specific shocks. We also assume that productivity follows a random walk with the idiosyncratic shock $z_{i,t}$ where $A_{i,t} = A_{i,t-1} + z_{i,t}$ and $z_{i,t} \sim N(0, \sigma_z)$. The firm's state-level information is represented by it's price-gap

$$x_{i,t} = p_{i,t} - p^*_{i,t} \tag{2}$$

where $p_{i,t}$ is the price of the item sold by firm $i$. Clearly, when $p_{i,t} = p^*_{i,t}$ there is no price-gap as the firm has already priced the item at its optimal price. The hazard function depends on $x$, the probability a firm will adjust their prices depends on the price-gap. We modify the functional form of the piecewise linear hazard function used by Karadi et al. (2024) to better represent high trend inflation.

$$\Lambda(x) = \begin{cases} a + be^{-x} & \text{if } x < 0 \text{ and } a + be^{-x} \leq 1 \\ a + cx & \text{if } x \geq 0 \text{ and } a + cx \leq 1 \\ 1 & \text{otherwise} \end{cases} \tag{3}$$

In a high inflation environment, the relationship between a positive price-gap and the probability of adjustment becomes non-linear. When the price-gap is negative, the probability of adjustment decreases exponentially as the price-gap goes toward zero. The parameter $b$ captures the rate of decay of the probability of adjustment as the price-gap approaches zero. This captures the idea that firms are more likely to adjust their prices when they are far from their optimal price regardless of the gap difference. When the price-gap is zero the probability of adjustment suddenly falls to $a$ which is the baseline hazard. This is because firms are less likely to adjust their prices when they are close to their optimal price. The parameter $c$ captures the rate of increase in the probability of adjustment as the price-gap widens. In this domain the probability of adjustment increases linearly with the size of the price-gap. This reflects the fact that firms are less likely to adjust their prices when they are close to their optimal price, but they will adjust more aggressively as the price-gap widens.

Furthermore, we incorporate the trend inflation into the baseline hazard parameter $a$. Let $\theta_i$ denote the expected inflation of the firm $i$. Firms independently and identically draw $\theta \sim N(0, \sigma_\theta)$. Given a price-gap $x$, the size of the price adjustment is defined as a piecewise linear function

$$\mathit{\Delta}(x) = \begin{cases} -\alpha(x - \theta) & \text{if } x < \theta \\ \beta x & \text{if } x \geq \theta \end{cases} \tag{4}$$

where $\alpha$ is the ratio between price adjustment and the price-gap for negative gaps, and $\beta$ is the ratio for positive gaps. The piecewise linear function captures the fact that firms adjust their prices more aggressively when they are far from their optimal price. Furthermore, $\theta$ skews the kink point of the piecewise linear function to the right. This represents the fact that in a high inflation environment, firms with higher inflation expectations are more likely to adjust their prices even if the competitor-price gap is within the neighborhood of zero.

The baseline hazard for each firm $i$ is then defined in the following manner:

$$a_i = \mu(1 + \theta_i)$$

where $\mu$ is the true parameter value of the drift in the random walk of trend inflation which is common across all firms. Since the baseline hazard represents the probability of price adjustment even when the price-gap is zero, it is scaled by the expected inflation of the firm. This means that firms with higher inflation expectations are more likely to adjust their prices even if the price-gap is zero.

Using (2) and (3) we define inflation as

$$\pi = \int \Delta(x)\Lambda(x)f(x)dx \tag{5}$$

where $f(x)$ is the density of price-gaps across firms at time $t$. (5) effectively calculates the aggregate inflation it consider the aggregate price adjustment size, $\Delta(x)$ based on the probability of adjustment $\Lambda(x)$ across the price gap distribution.

## 3 Data

The data used for this analysis was collected daily between 2020 and 2024 from Marul[1], an online platform where consumers can purchase and have their groceries delivered from

[1] Although the platform is no longer operational, an archived version can be found at https://web.archive.org/web/20191008091416/https://www.marul.com/tr/

nearby supermarkets. The use of Marul as a data source allows for the collection of prices of identical goods across different markets within the same region. Our dataset primarily consists of supermarkets in Istanbul and Ankara. Since this data was web scraped, there are inevitable jumps in the continuity of the data from interruptions in the scraping process. Similarly, sometimes the script would misreport the correct price (i.e., the true price is 9.99, however, 999 is recorded). In order to mitigate the influence of price outliers, the upper and lower 2.5% percentiles of prices were dropped from the data. After cleaning the data and dropping observations identified as sales, the final size of the dataset is $n = 48,770,717$ observations across 70 markets, $26,480$ items, and 67 categories (Table 1).

Table 1: Summary Statistics

| Statistic | Value |
|---|---|
| Mean Price | 17.44 |
| Standard Deviation Price | 15.37 |
| Number of Markets | 70 |
| Number of Items (Code) | 26,480 |
| Number of Categories (Item) | 67 |
| Minimum Price | 1.45 |
| Maximum Price | 84.90 |
| Median Price | 12.95 |
| Total Observations | 48,770,717 |

Akin to Karadi et al. (2024), we compute the mode of each item's price in each store for each month to define its reference price. All subsequent price related calculations are based on this store–item–month reference price. For example, the average competitor-price is the mean of the reference prices of all other stores selling the same item in the same month. The price-gap between a store and its competitors is measured as the percentage difference between the store's reference price and the average competitor-price for the same item. A price adjustment is defined as the percentage change in a store–item pair's reference price between two consecutive months, given there was a competitor-price gap in the initial month.

Table 2 summarizes the observed price adjustments in our data. Approximately 20% of competitor-price gaps are followed by a price adjustment in the subsequent month. This is about twice as high as the rate documented in the U.S. (Karadi et al. 2024), however, given the high degree of price volatility in Turkey during our sample period, this result has empirical merit. The magnitude of price increases exceeds that of price decreases by roughly 34.4%, indicating that overall price changes are driven by price increases. This pattern is reinforced by the fact that the frequency of price increases is nine times greater than that of price decreases. Furthermore, the kurtosis of price changes is extremely high at 10.33, suggesting a distribution that is sharply peaked around the mean with heavy tails. Karadi et al. (2024) also report high kurtosis in the U.S. however, the magnitude observed here is substantially larger, indicating greater volatility in Turkish price changes.

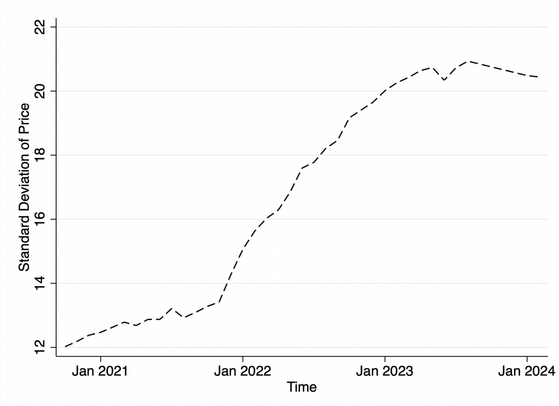
Table 2: Price Adjustment Statistics

| Statistic | Value |
|---|---|
| Total price-gap Observations | 1,487,246 |
| Frequency of Price Adjustments | 20.2% |
| Standard Deviation of Price Changes | 12.68% |
| Mean Size of Price Change Increases | 16.42% |
| Mean Size of Price Change Decreases | -12.22% |
| Frequency of Price Increases | 91.0% |
| Frequency of Price Decreases | 9.0% |
| Kurtosis of Price Changes | 10.33 |

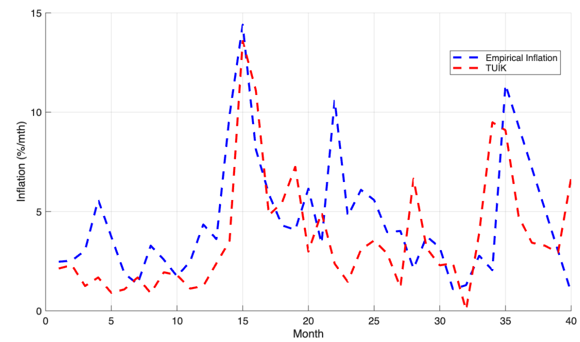
Figure 1a further illustrates the volatility in prices. The slope of the standard deviation of price over time is highest starting beginning in January 2022, immediately following the Turkish Central Bank's announcement of the foreign currency–protected deposit scheme in December 2021. Figure 1b plots the average absolute price change over time, where price changes are measured not conditional on a competitor-price gap, but as average month-to-month change. For comparison, we also include the monthly Consumer Price Index (CPI) from the Turkish Statistical Institute (TUİK)[2] for the months covered in our data. Due to missing observations in some months, we applied linear interpolation using standard time-

[2]See https://www.tcmb.gov.tr/wps/wcm/connect/EN/TCMB+EN/Main+Menu/Statistics/Inflation+Data/Consumer+Prices

series methods, so portions of the figure are based on interpolated rather than directly observed data. In months with where we have more observations in our data, our estimate closely tracks official inflation. However, in months with fewer observations, alignment is weaker.




(a) Standard deviation of prices over time

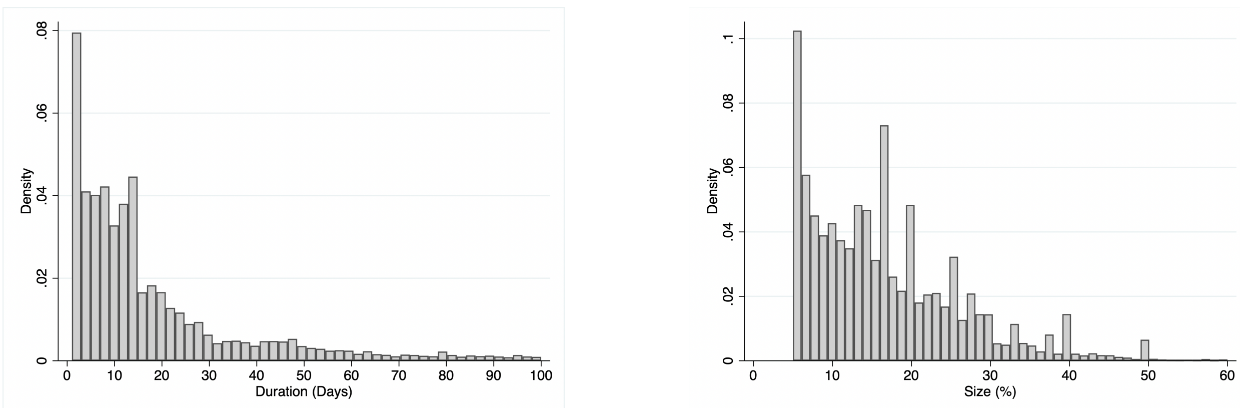



(b) Absolute price change over time

Figure 1

### 3.1 Sales Filtering

Furthermore, we use the V-shape sales filtering method to identify the sales in the data (Nakamura and Steinsson 2008). Since, our data is scraped at the daily level, we do not have the empirical concern of Nakamura and Steinsson (2008) of a regular price change occurring immediately after the identification of a V-shaped price movement. We did not restrict the time window for detecting a V-shaped pattern, allowing the duration of an identified sale to span multiple months. Finally, if the price of an item decreased and then increased and if the new price is within 5% of the old price this is still counted as a sale i.e after a V-shaped movement the two prices do not need to be exactly equal. This is to account for any slight price adjustments or minor errors in the data collections as mentioned previously. About 5% of the observations in the data were classified as sales. The average sale lasted about 23 days. However, as seen in Figure 2a the distribution of sale duration is heavily skewed to the right. This means that a lot of the sales in our data are short-lived sales. The median sale size was about 17% which is consistent with the results in the United States (Hitsch et al. 2021). Again, the distribution of discount size is also right-skewed meaning Turkish grocery store retailers were less likely to have larger discounts (Figure 2b). While some studies consider sales as a mechanism for firms to adjust prices during business cycle fluctuations (Kehoe and Midrigan 2015, Anderson et al. 2017, Kryvtsov and Vincent 2021), there is also strong evidence that sales inflation does not respond significantly to aggregate shocks (Karadi et al. 2021, Gautier et al. 2024). The distribution of sale duration and magnitude in our data indicates that focus on the reference prices of each market is sufficient for our analysis.



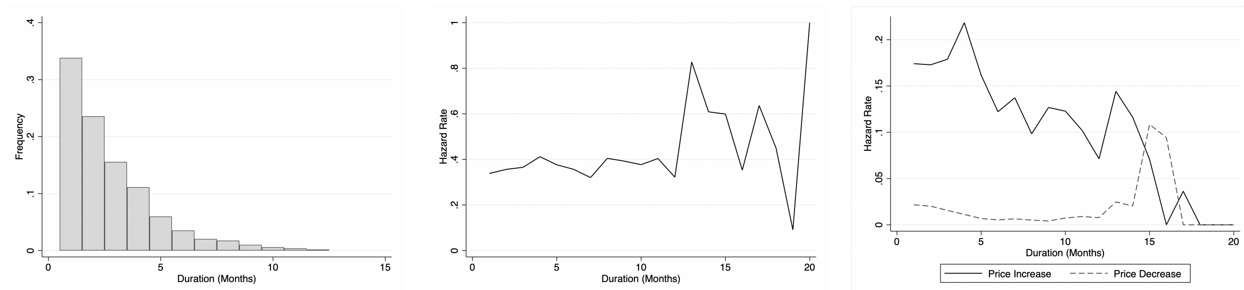

(a) Distribution of sale duration

(b) Distribution of sale size

Figure 2

### 3.2 Price spells and hazard rates

We examine the empirical distribution of unconditional price spells and the corresponding hazard rates over time. An unconditional price spell is defined as the number of consecutive months a store maintains the same price before any change occurs. The hazard rate measures the conditional probability that a price changes in a given month, conditional on the spell having lasted until that month. In our data, the average price spell is approximately two months, with frequency declining monotonically as duration increases (Figure 3a). This pattern is consistent with the high inflation environment in Turkey, where long price spells are unlikely to be sustained. The hazard rate remains relatively stable across most of the distribution, but exhibits a pronounced spike around month 12 (Figure 3b), reflecting the behavior of firms that systematically revise prices on an annual basis. This seasonal spike is consistent with empirical evidence from other countries documenting similar end-of-year adjustments (Álvarez et al. 2005). Finally, we decompose the aggregate hazard rate into price increases and price decreases (Figure 3c). The results indicate that the overall hazard pattern is primarily driven by price increases, whereas price decreases occur far less frequently.




(a) Distribution of unconditional price spells

(b) Price change hazard

(c) Decomposed price-change hazard (price increases and decreases)

Figure 3: Price spells and hazards.

## 4 Empirical Results

This section generates the empirical results of the adjustment size function, the hazard function, and the density of the competitor-prices gaps. We also specify the fixed-effects methodology to deal with persistent heterogeneity in at the store, category, and time level.

### 4.1 Estimation of price-gap proxy

Estimating the adjustment size function and hazard function requires an optimal price level as gaps are defined by $x_t = p_t - {p_t}^*$. However, since we cannot observe the optimal price level in the data, we use the competitor-price gap as a proxy for determining deviations from the optimal price level. The competitor-price gap is defined as the difference between the price of a good at a store and the average price of that good across all other stores in the same market. This is the same proxy used by Karadi et al. (2024) which is proven to be a robust method. In order to calculate the observed gaps in the data, we first collapse the data to the store-item-month level. This is done by calculating the reference price[3] (mode of all prices in a given month) of each good at each store in each month. Then for each store-item-month observation, we calculate competitor-price average as the average of the reference prices of all other stores selling the same item. Next, competitor-price gap is generated by simply taking the difference between the reference price of the store and the competitor-price average for each store-item-month observation. Finally, we estimate three fixed effects for each observation: (1) store-category fixed effects, (2) store-item fixed effects, and (3) store-month fixed effects. The store-category fixed effects control for the persistent heterogeneity of the store generally updating prices of a given category. The store-item fixed effects control for how often the store generally updates the price of the item, while the store-month fixed effects control for how often the store updates prices in a given month independent of the item or category. We estimate the price-gap $x_{sit}$ for each store $s$, item $i$, and month $t$ in two steps. First, we reformulate $x_{sit}$ by subtracting the store-category fixed effects from the observed competitor-price gap $x^{\circ}_{sit}$ for each store-item-month: $x_{sit} = x^{\circ}_{sit} - \alpha_{sc}$. We then estimate the panel level fixed effects through the following regression:

$$x_{sit} = \alpha_{is} + \alpha_{st} + \epsilon_{sit} \tag{6}$$

where $\alpha_{is}$ is the store-item fixed effect, $\alpha_{st}$ is the store-month fixed effect, and $\epsilon_{sit}$ is the error term, and is effectively the normalized price-gap. Figure 4 shows the distribution of the normalized price-gap across all store-item-month observations.

### 4.2 Size of price adjustment

Once we have the normalized price-gaps, we can then determine the adjustment size of each store-item-month observation in response to a gap. If there is a non-zero gap at time $t$,

[3] Karadi et al. (2024) uses log price, however given the nature of volatility in our data, using the actual prices allowed for more robust estimates.

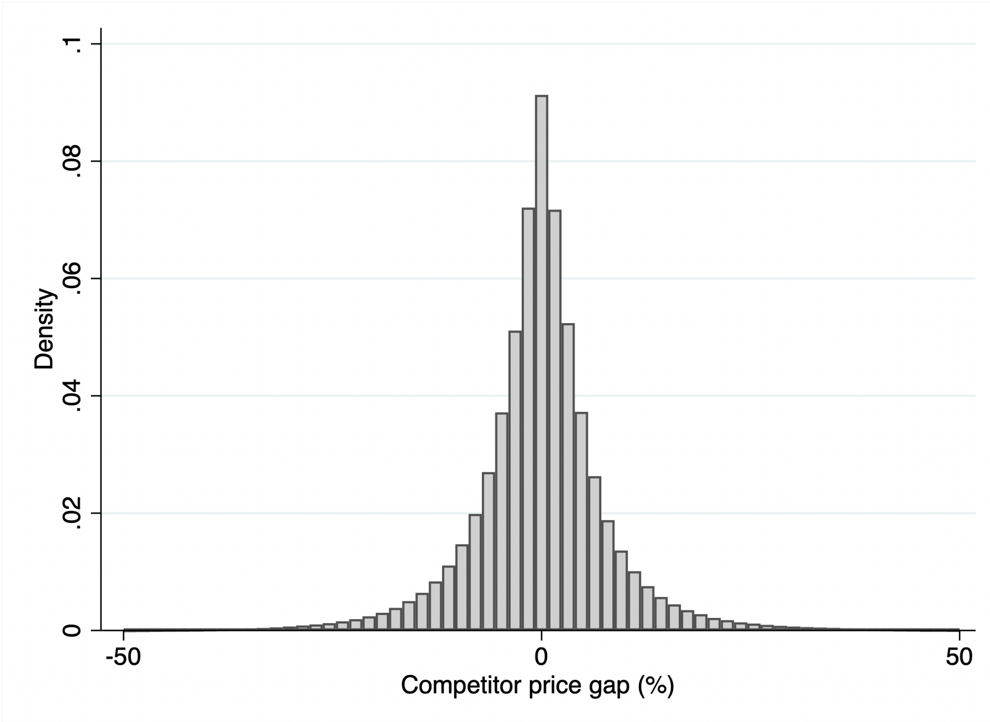



Figure 4: Distribution of competitor-price gap

we check if the reference price of the store-item pair at time $t + 1$ is different from the reference price at time $t$. If it is, we record this as an adjustment and calculate the percent change in the reference price as the adjustment size. In total there were $1,487,246$ observed price-gaps in the data, and about 20% of these gaps were followed by a price adjustment. Figure 5 plots the average adjustment size against each observed price-gap bin. For negative gaps, the relationship is negative and nearly one-to-one: larger negative gaps are followed by proportionally larger positive price adjustments, up to the point where the gap turns positive. In contrast to Karadi et al. (2024), this tight relationship does not persist for positive gaps. Instead, the average adjustment size remains close to zero even when the price-gap is positive. This asymmetry provides a novel contribution that, in a high inflation context, firms primarily respond to being priced below competitors, as they seek to avoid lagging behind in relative price levels. Once the gap passes a certain positive threshold, firms rarely reduce prices. In such environments, lowering prices entails menu costs without lasting benefit, as inflation will likely push prices upward in the next period. The threshold at which this flattening occurs aligns with the model's expected inflation parameter, $\theta$. Consistent with this, the kink point in the empirical distribution is shifted to the right of zero, indicating that even when not lagging behind competitors, firms may still increase prices if they anticipate higher inflation in the following period.

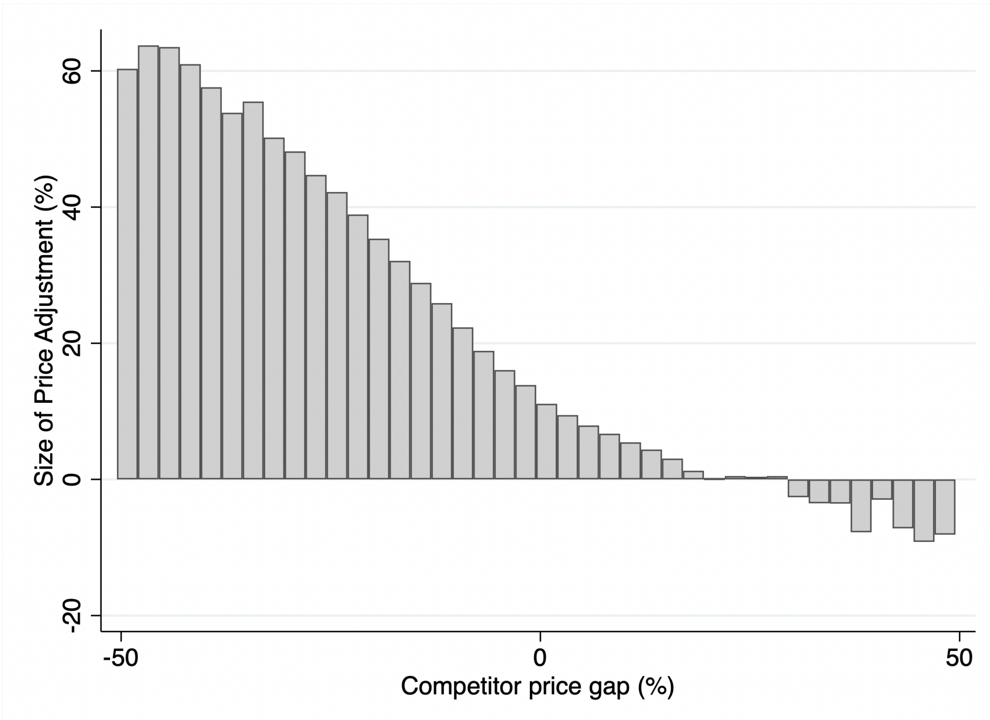



Figure 5: Average Size of Adjustment Given Competitor price-gap

### 4.3 Price adjustment hazard

The empirical state-dependent hazard function is computed by dividing the number of price adjustments observed in each competitor-price gap bin by the total number of observations in that bin. Karadi et al. (2024) find a symmetric, V-shaped, piecewise linear hazard function, reflecting their one-to-one adjustment size distribution as firms with prices both above and below their competitors are equally likely to adjust in order to reset the competitor-price gap to zero. In contrast, our results reveal an asymmetric and non-linear V-shaped relationship (Figure 6). When the price-gap is negative, the probability of adjustment is high and largely invariant to the magnitude of the gap. As the gap approaches zero from below, the adjustment probability declines exponentially toward the baseline hazard rate $a$. For positive gaps, the adjustment probability increases approximately linearly with the gap size, but the slope is small, indicating that firms raise prices more readily than they reduce them. This pattern aligns with the adjustment size results: firms priced below their competitors tend to reset their prices toward the competitor level, whereas firms priced above are less likely to reduce their prices. The estimated baseline hazard rate is substantially higher than in Karadi et al. (2024), consistent with the notion that, in a high inflation environment, firms are more likely to adjust prices even when they are close to their optimal level.

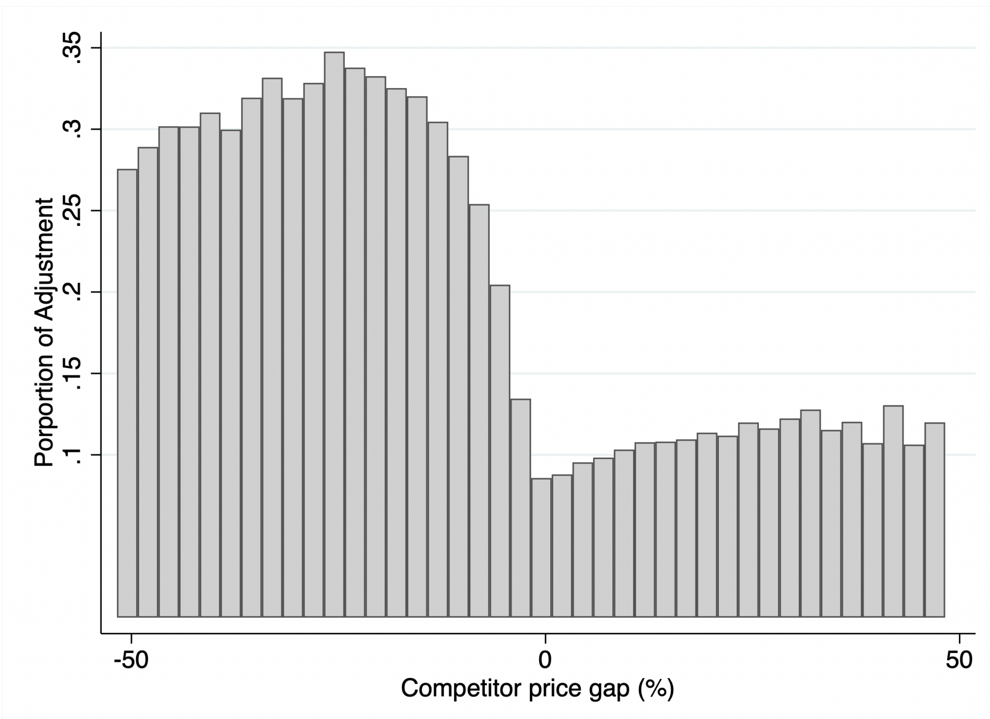



Figure 6: Probability of price adjustment given competitor-price gap

## 5 Inflation Simulation

To assess whether the model effectively captures trend inflation, we use various empirical moments to calibrate the model parameters and simulate inflation over time. While the model of Costain and Nakov (2011) considers households, labor markets, and money in the economy, we focus on the price-setting mechanism and the adjustment dynamics of firms.

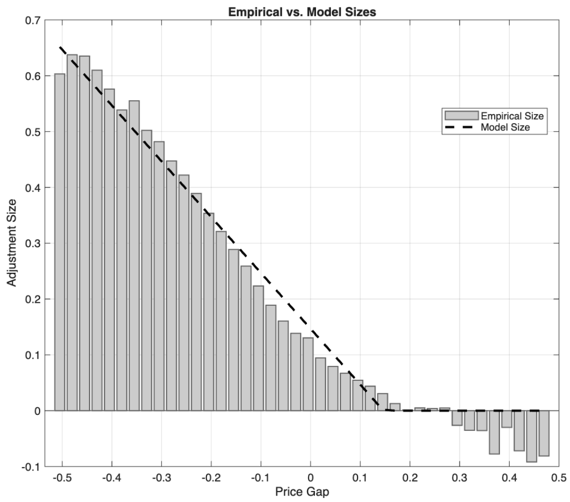
Table 3 contains the results of the calibration.

### 5.1 Calibration

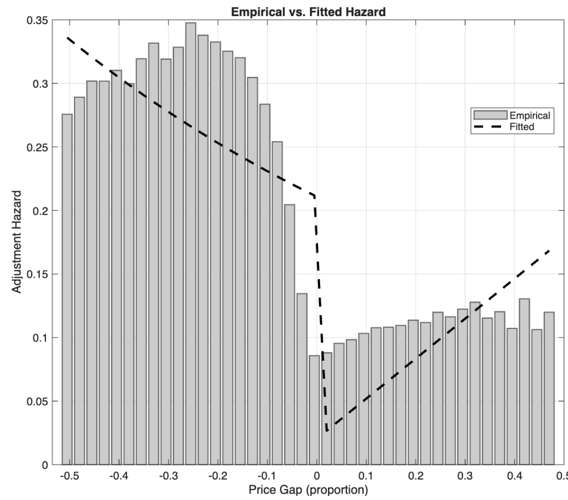
We first calibrate the parameters $\alpha$, $\beta$, $\theta$ using the adjustment size function in equation (4). The empirical moments used include the distribution of price-gaps, the mean percentage change in adjustment size, and the standard deviation of price changes. Figure 7a shows the calibrated adjustment size function overlaid on the empirical results. The slope parameter for negative price-gaps is estimated at $\alpha = 0.999$ up to the kink point $\theta = 0.147$. Beyond this point, the estimate $\beta = 0.001$ indicates that the average adjustment size for positive gaps is effectively zero. This implies that price adjustments are nearly one-to-one with the gap when prices are below competitors, but minimal when prices are above competitors. Since in the model each firm draws an inflation expectation distortion parameter $\theta$, we also calibrate the standard deviation of $\theta$, obtaining $\sigma_\theta = 0.372$, by fixing $\alpha$, $\beta$, and $\theta$ at their estimated values and simulating $n = 10{,}000$ Gauss–Hermite quadrature draws to match the empirical adjustment size distribution.

Next, we estimate the parameters $b$, $c$, and $\mu$ of the hazard function using the mean absolute size of price adjustments, the total frequency of adjustments, and the distribution of price-gaps as calibration moments, along with the estimate of $\theta$ obtained from calibrating the adjustment size function. We do not explicitly calibrate $a$, as it is determined by $\mu$ and $\theta$. Figure 7 compares the calibrated hazard function to the empirical estimates. The rate of convergence of the hazard from negative gaps toward zero is estimated at $b = 0.190$, indicating a relatively gradual decline in the probability of adjustment as firms approach their optimal price from below. For positive gaps, the slope parameter $c = 0.315$ implies a modest increase in adjustment probability as prices rise above competitors, consistent with the asymmetry documented in the empirical hazard. The drift term is estimated at $\hat{\mu} = 0.017$, capturing the average monthly trend inflation in the model.

Finally, we estimate the standard deviation of the inflation trend's random walk, $\sigma_\epsilon$, by




(a) Calibration of size adjustment function




(b) Calibration of hazard function

Figure 7

regressing the absolute size of the price change at time $t$ on its lagged value, $|\Delta p_{t-1}|$, and the estimated drift $\hat{\mu}$. The standard deviation of the residuals yields $\sigma_\epsilon = 0.030$. We do not calibrate the idiosyncratic productivity shock, $z_{i,t}$, as it is not a key parameter in the model. Instead, we adopt the value used by Karadi et al. (2024), $\sigma_v = 0.044$.

Table 3: Estimated Model Parameters

| Parameter | Estimate |
|---|---|
| $\alpha$ | 0.999 |
| $\beta$ | 0.001 |
| $\theta$ | 0.147 |
| $\sigma_{\text{gap}}$ | 0.156 |
| $b$ | 0.190 |
| $c$ | 0.315 |
| $\mu$ | 0.017 |
| $\sigma_\epsilon$ | 0.030 |
| $\sigma_\theta$ | 0.372 |
| $\sigma_v$ | 0.044 |

### 5.2 Simulation results

We simulate month-to-month inflation dynamics with $N = 1{,}000$ firms over $T = 40$ periods, matching the length of our empirical dataset. At $t = 0$, each firm draws a distortion parameter $\theta_i \sim \mathcal{N}(0, \sigma_\theta)$, which determines its firm-specific baseline hazard. Initial price-gaps are drawn from $x_{i0} \sim \mathcal{N}(0, \sigma_{\text{gap}})$, where $\sigma_{\text{gap}}$ corresponds to the empirical standard deviation of competitor-price gaps.[4]

In each period, aggregate trend inflation and firm-level productivity evolve according to the stochastic processes defined in the model. Given the resulting price-gap $x_{it}$, each firm evaluates its adjustment probability via the hazard function $\Lambda_i(x_i)$. If a uniform draw falls below this threshold, the firm adjusts its price using the adjustment size function $\Delta(x_{it})$, and updates its posted price accordingly. The simulation proceeds iteratively until $t = 40$.

Figure 8 presents the average simulated inflation path across 1,000 Monte Carlo repetitions, along with the empirical inflation series from our dataset and the official Turkish Statistical Institute (TUİK) figures. The shaded region denotes the 95% confidence interval of the simulation. The model successfully reproduces both the level and dispersion of inflation observed in the data. Simulated month-to-month inflation fluctuates between 1% and 15%, closely aligning with the volatility range of the empirical distribution.

## 6 Conclusion

This paper provides new evidence on firm price-setting behavior in high inflation environments using a novel dataset of 48.8 million daily price observations from Turkish grocery retailers during 2020-2024. Our analysis reveals fundamental asymmetries in both the timing and magnitude of price adjustments that challenge existing state-dependent pricing models calibrated to low inflation contexts. These findings highlight how high inflation alters firms' incentives, contrasting existing state-dependent pricing models calibrated to low inflation contexts (Karadi et al. 2021, Karadi et al. 2024).

We document three empirical findings from our analysis. First, price adjustments are strongly asymmetric: firms respond almost one-for-one to negative competitor-price gaps

[4]See Figure 4.

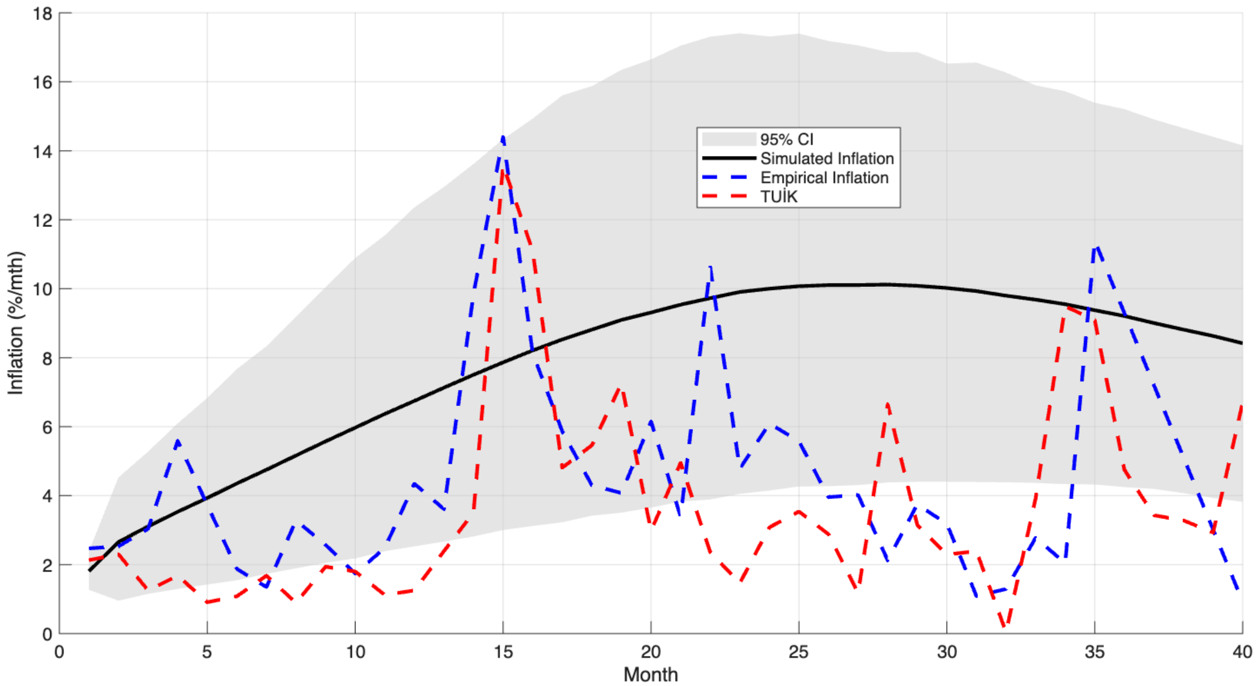



Figure 8: Probability of price adjustment given competitor-price gap

($\alpha = 0.999$), but make minimal adjustments for non-extreme positive gaps ($\beta = 0.001$). Second, the state-dependent hazard function is asymmetrically V-shaped, with adjustment probabilities remaining high for negative gaps (25-35%) and only marginally increasing for positive gaps. Third, inflation expectations shift the kink point in the adjustment size function rightward by approximately 14.7%, indicating anticipatory price increases even when competitively aligned with competitors.

We extend a state-dependent pricing framework to incorporate these features, calibrating the model to match empirical moments from the data. The model replicates the observed asymmetry in adjustment size and frequency, and it generates inflation dynamics consistent with both the magnitude and volatility of Turkish monthly inflation over the sample period in our data. These results suggest that high inflation environments influence firms' price-setting incentives, increasing responsiveness to being priced below competitors while reducing the likelihood of price decreases, even when prices are above competitors.

Our findings have implications for the modeling of price adjustment in high inflation economies.

Standard symmetric hazard specifications, which fit well in low inflation contexts, may misrepresent inflation dynamics when menu costs interact with persistent inflationary pressures and asymmetric incentives. Policymakers seeking to understand inflation persistence in such settings should account for the fact that downward price flexibility is limited, even when relative prices are misaligned.

The analysis is subject to certain limitations. While our data allow for precise measurement of within-market price-gaps and adjustments, they are restricted to two metropolitan areas and to the grocery retail sector, which may limit generalizability to other sectors or regions. In addition, our model abstracts from potential strategic complementarities beyond direct competitor-price gaps, as well as from inventory or supply chain considerations that may also influence adjustment behavior.

Future research could extend the framework of the model along several dimensions. First, allowing for time-varying shocks to the inflation-expectation parameter, $\theta$, would better capture the evolution of firms' expectations over time. In this paper, we hold $\theta$ fixed in order to focus on the state-dependent dynamics arising from competitor-price gaps. Second, combining micro price data with direct firm-level expectation surveys would enable sharper identification of the role of inflation expectations in shaping adjustment thresholds. Finally, embedding the asymmetric hazard and adjustment-size functions into a full DSGE model with monetary policy shocks could quantify the welfare and policy implications of these behavioral patterns.

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