Selection Effects in Retail Chain Pricing

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October 26, 2021

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Abstract

This paper examines the effect of retail chain price synchronization on monetary non-neutrality—the extent to which nominal shocks have real effects on the economy. In standard menu cost models, firms optimally choose the timing of their price changes also known as the *selection effect*. I extend a standard menu cost model to analyze selection effects in retail chain pricing. The extended model is calibrated to match retail chain price synchronization statistics using scanner-level data for over 600 goods. I find that the retail chain model more than doubles the degree of selection effects—as measured by the store's price elasticity to the aggregate price level—relative to the standard menu cost model. This relationship suggests that the standard menu cost model overestimates the degree of monetary non-neutrality by ignoring synchronization in retail chain pricing.

Keywords: Uniform Pricing, Inflation, Selection Effects
JEL Classifications: E3, L11

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1 Introduction

Selection effects—the concept that firms optimally choose the timing of their price changes—are a key determinant in how the economy responds to aggregate shocks. As selection increases, firms respond more to aggregate shocks which mitigates their impact. This paper examines the extent of selection effects in the context of retail chain pricing.

It is commonly assumed in economic models that firms act independently. However, stores belonging to the same retail chain (e.g. Kroger, Publix) set nearly identical prices in practice. Additionally, retail chains synchronize the timing and magnitude of their price changes across stores violating the independence assumption.

This paper extends an otherwise standard menu cost model to account for retail chain price synchronization.[1] I show that accounting for retail chains more than doubles the degree of selection relative to the standard menu cost model. The intuition behind this result lies in the store's pricing decision. In the standard model, stores decide whether or not to change their price contingent on their idiosyncratic productivity and their current price relative to the aggregate price level. Firms then change their price if the expected profit gains outweigh the menu cost.

Introducing retail chains to the model adds another component to the store pricing decision. First, store-level productivity shocks include a common retail chain component. This common component helps account for the price synchronization seen in the data for stores belonging to the same chain. I also assume that the retail chain occasionally sets the store's price. However, when determining the store's price, the retailer cannot observe the store's productivity and thus chooses the store's price based on the retailer-level productivity. The combination of these two assumptions lead to the amplified selection effect in the retail chain model.

Pricing in this environment can be interpreted as a two-step process. First, the retailer

[1] See Sheshinski and Weiss (1977); Golosov and Lucas (2007). The baseline model in this paper closely follows Nakamura and Steinsson (2008).

sets a target price for all stores belonging to its chain using chain-level state variables. Second, stores choose to keep the retail chain price or set their own price. The assumptions above serve as a reduced form modelling approach for the cost that a store pays to deviate from the chain price. Thus, firms in the retail chain model face a "constrained" optimization problem whereas firms in the standard model are "unconstrained". This constraint causes stores to be less responsive to their idiosyncratic productivity shocks (as it is more costly) and more responsive to aggregate shocks.

I estimate selection effects by simulating both the standard model and retail chain model calibrated to scanner-level data for over 600 goods sold in the United States from 2001-2007. Data come from Information Resources Inc. (IRI) which records the weekly revenue and quantity sold for each product at the store level. Importantly, the dataset records the retail chain that each store belongs to.

Before calibrating the model, I document descriptive evidence of retail chain price synchronization. I begin by documenting synchronization in the timing of price changes. I find that if one store in a retail chain changes their price in a given week, there is a 70% probability that at least half of stores within that chain change their price during the same week. The conditional probability remains over 40% with the increased restriction that all stores within the chain change prices. Requiring that all price changes be in the same direction yields an estimate of about 30% for both price increases and decreases. I also find that these price changes are similar in magnitude. A variance decomposition shows that 62% of price dispersion from a store's average price can be explained by chain-week fixed effects on average over goods while the idiosyncratic store component accounts for only 25% of price variation. This result is prevalent across most goods with the chain-week component explaining at least half of the price variation for 625 of the 655 goods in the sample.

The retail chain model is then calibrated to match several price-setting statistics including the chain-week component of the variance decomposition for each good. Thus, the empirical variance decomposition serves as a key factor in determining the probability that a retail chain sets an individual store's price in the model (i.e. the degree of the retail chain "constraint"). I then simulate store-level price paths for each of the 655 goods using the retail chain model. After simulating the retail chain model, I perform a counterfactual analysis where stores do not adhere to the retail chain constraint. Each store faces the same inflation process and analogous productivity process as in the retail-chain simulation. Thus, differences between the models are not driven by different productivity draws and are solely driven by each store selecting its unconstrained optimal price in each period.

I measure selection by regressing the change in a store's log price on the change in the aggregate price level controlling for changes in store-level productivity. The partial equilibrium nature of the model facilitates this regression as store-level price changes do not feedback into the aggregate price level which follows an exogenous process. The coefficient on the aggregate price level thus serves as an estimate of the responsiveness of store-level prices to exogenous changes in the aggregate price level (i.e. the selection effect). The weighted mean estimates for the retail chain model and standard model are 0.25 and 0.09, respectively. These estimates suggest that a 1% increase in the aggregate price level leads to a 0.25% increase in a store's price on average.

These results build on an extensive literature that analyzes selection effects in sticky-price models. The Calvo (1983) model of price adjustments represents one extreme in sticky price models. In the Calvo model, a subset of firms are selected at random each period to change their price. Thus, as noted in Nakamura and Steinsson (2013), firms cannot optimally time their price changes, and aggregate shocks have no effect on how many and which firms change their price. Caballero and Engel (2007) illustrate that aggregate shocks only affect the intensive margin of price adjustment in the Calvo model (i.e. only the magnitude of price changes is affected for firms that were already going to adjust their price) which leads to large real effects of monetary shocks.

Menu cost models such as the one in this paper introduce an extensive margin of price adjustment (Caballero and Engel, 2007). Thus, aggregate shocks also affect how many and *which* firms change their price referred to as the selection effect in Golosov and Lucas (2007). In general, the extensive margin of adjustment leads nominal shocks to have less real effects on the economy compared to the Calvo model. For example, nominal shocks only produce 20% of the real effects in Golosov and Lucas (2007) compared to the Calvo model. However, the extent of the real effects varies significantly depending on the modelling assumptions used. Golosov and Lucas (2007) commonly serves as the lower bound where additional assumptions typically predict effects closer to those in the Calvo model (Leptokurtic shocks and scale economies: Midrigan (2011), Alvarez and Lippi (2014), Bonomo et al. (2020); Random menu costs: Dotsey et al. (1999); Sectoral heterogeneity: Nakamura and Steinsson (2010)).

In contrast to the examples above, my results suggest that retail chain pricing decreases the real effects of nominal shocks. Nakamura and Steinsson (2010) help illustrate the intuition for this result in menu cost models. They show, for a given frequency of price change, reducing the variance of stores' idiosyncratic productivity shock leads to less real effects of nominal shocks. This is a result of the average inflation rate becoming a more important determinant in stores' pricing decisions. Golosov and Lucas (2007) also illustrate this result and show that their setup converges to Caplin and Spulber (1987) in the absence of idiosyncratic shocks. The Caplin and Spulber (1987) model represents the opposite extreme of the Calvo model in which the aggregate price level is completely flexible even in the presence of micro price stickiness. Thus, nominal rigidities have no real effect on the economy. Although the partial equilibrium nature of the model does not allow me to directly estimate the real effects of nominal shocks, I show that my regression specification captures the relationship described by Nakamura and Steinsson (2010) and Golosov and Lucas (2007) in the standard menu cost model. This relationship suggests that the standard menu cost model overestimates the degree of monetary non-neutrality by ignoring synchronization in retail chain pricing as illustrated by my regression results.

This paper also builds on the literature of retail chain pricing. DellaVigna and Gentzkow

(2019) and Adams and Williams (2019) show that chains often set prices uniformly across stores or according to a small set of retail pricing zones. Similarly, online and offline prices for a given retailer tend to be synchronized (Cavallo, 2017, 2019). Previous studies have found that chains predominantly account for price-level differences and variation in the frequency of price changes (Daruich and Kozlowski, 2021; Nakamura et al., 2011). The variance decomposition in this paper is most closely related to that in Nakamura (2008) which focuses on time series variation in prices and finds similar results.

Lastly, this paper helps provide a rationale for the stickiness of local prices to local conditions (Daruich and Kozlowski, 2021; Gagnon and López-Salido, 2020; DellaVigna and Gentzkow, 2019). This paper is most closely related to Daruich and Kozlowski (2021) who develop a model of multi-region firms with uniform pricing. Their paper finds that local elasticities are likely biased estimates of aggregate elasticities when accounting for uniform pricing in retail chains. My paper does not explicitly examine the impact of retail chain pricing on regional versus aggregate shocks. Instead, my paper highlights the degree of selection effects with versus without synchronization in retail chain pricing. As retail chain synchronization increases, stores respond less to their idiosyncratic shocks and respond more to aggregate shocks which helps rationalize the effects found in Gagnon and López-Salido (2020).

The rest of the paper proceeds as follows. Section 2 describes the IRI scanner dataset. Section 3 presents descriptive statistics of price synchronization within retail chains. Section 4 introduces the standard menu cost model and the retail chain extension. Section 5 uses model simulations to estimate selection effects. Section 6 concludes.

2 Data

My primary analysis uses the Information Resources Inc. (IRI) retail scanner dataset from 2001-2007. The IRI records the total weekly revenue and quantity sold for over 100,000 products and 3,000 stores.[2] Products are defined by their Universal Product Code (UPC), and stores are defined as a key provided by the IRI. The average price of product i in store j for the week t is computed as the total revenue (Rev_{ijt}) divided by total quantity sold (Q_{ijt}), $P_{ijt} = \frac{Rev_{ijt}}{Q_{ijt}}$.

2.1 Sample Formation

2.1.1 Stores

The IRI provides data for both grocery and drug stores. My primary sample consists only of grocery stores which are a majority of the dataset. Each grocery store may belong to a specific retail chain (e.g. Kroger, Publix). In order to analyze the effect of retail chain pricing, I require that stores (1) belong to a retail chain, (2) do not switch chains over time, (3) and are open for more than one year.

Panel A of Table 1 highlights the effects of these requirements. The first restriction facilitates the variance decomposition presented in the next section. Only 11 of the over 2,000 grocery stores in the dataset do not belong to a retail chain. The second restriction helps account for pricing behavior related to retail chain switching and reduces the number of stores in the sample by one-third. DellaVigna and Gentzkow (2019) conduct an event-study analysis and show that pricing behavior shifts substantially when stores switch chains which could bias the results of the variance decomposition. The final requirement that stores remain open for more than one year helps to remove pricing decisions that may be related to the opening and closing of a particular store. Overall, the store requirements have a strong effect on the total number of stores which reduce from 3,150 to 1,234. This effect is more modest for the number of retail chains which reduces from 147 to 101.

[2] A complete description of the dataset can be found in Bronnenberg et al. (2008).

Table 1: Summary Statistics of IRI Data

Panel A: Store Requirements					
	All Stores	Grocery Stores	Belong to Chain	Do not Switch Chain	In Sample > 1 Year
Number of Stores	3,150	2,378	2,367	1,534	1,234
Number of Chains	147	128	127	119	101

Panel B: Sample Formation					
	Stores	Chains	Products	Categories	Observations
Initial Sample	3,150	147	105,929	31	1,367,985,544
Store Requirements	1,234	101	91,102	31	656,570,883
Product Sold by at least half of Chains	1,184	99	7,342	31	360,875,433
Product Sold for at least half of store-weeks	1,123	99	655	29	60,698,877

Note: This table presents summary statistics of the IRI data. Panel A presents the effects of the store-level requirements on the total number of stores and chains in the sample. Panel B presents total counts for both stores and products throughout the complete sample formation.

2.1.2 Products

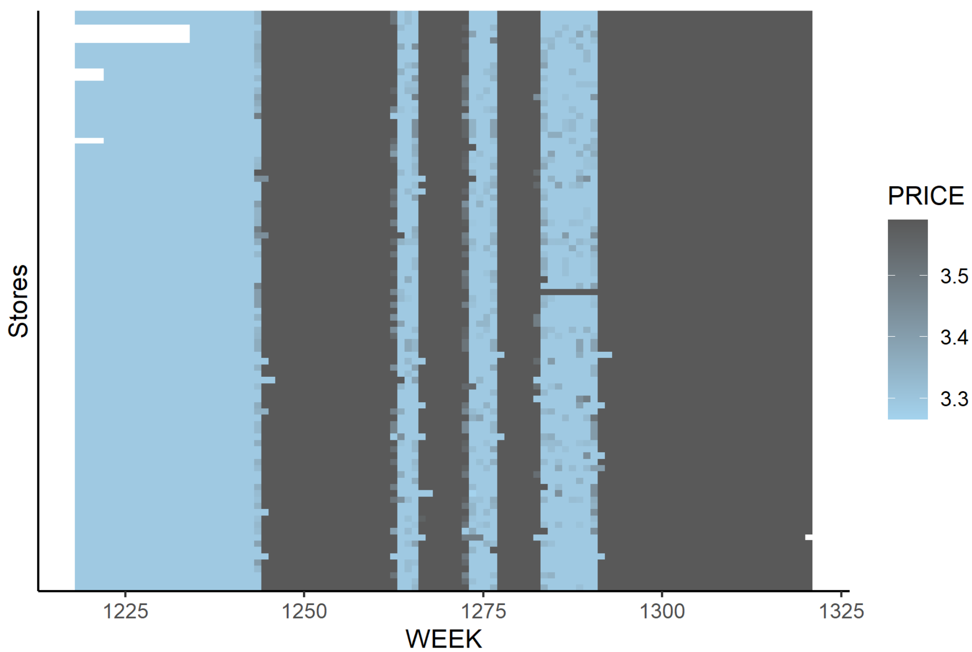
I further refine the sample through several product restrictions. I require that products (1) are carried by at least half of the chains and (2) are sold for at least half of store-weeks in a given year. These requirements help focus the sample on a set of widely available and commonly sold products. They also help avoid retail chain specific products.

Panel B of Table 1 documents the total effect of both the store and product requirements on the final sample of observations. The initial sample contained information for over 100,000 products. The store requirements had a relatively small effect on the total number of products (91,102) compared to the product requirements which reduced the final sample to 655 goods. The product requirements also removed about 100 stores. The final sample contains 1,123 stores belonging to 99 retail chains which sell 655 products across 29 categories.

2.2 Retail Chain Pricing

Importantly, the IRI dataset records the retail chain r that each store j belongs to. This allows me to document several stylized facts about retail chain pricing. The first fact is that retail chains implement uniform pricing—the phenomenon that stores belonging to the same

Figure 1: Example of Retail Chain Price Synchronization



Note: This figure plots an example of price synchronization within a retail chain. Each point on the y-axis represents an individual store belonging to the retail chain. Darker (lighter) shades represent higher (lower) prices. Missing values are represented by white space.

retail chain set nearly identical prices regardless of their respective market characteristics. Furthermore, the timing and magnitude of their price changes are often identical.

Figure 1 graphs an example of uniform pricing for a product belonging to the sugar/sugar substitute category within one retail chain. Each point on the y-axis represents an individual store belonging to the retail chain. Darker (lighter) shades represent higher (lower) prices. Missing values are represented by white space.

We see that there is small (or zero) price variation across stores for most weeks. Stores seldom make idiosyncratic price changes with most price changes occurring across all stores within the chain. Furthermore, prices change by the similar magnitudes across all stores. Appendix Figure A.1 illustrates that this pricing pattern is not limited to this specific good, nor the sugar/sugar substitute category.[3]

[3]Alternatively, see DellaVigna and Gentzkow (2019) for similar pricing patterns found in the Nielsen scanner dataset across various product categories.

3 Price Synchronization within Retail Chains

Figure 1 and Appendix Figure A.1 helped provide illustrative examples of price synchronization within retail chains across various products and product categories. This section attempts to quantify these illustrative examples. The first subsection documents stylized facts on the timing of price changes. The second subsection conducts a variance decomposition to help analyze both the direction and magnitude of price changes.

3.1 Price Synchronization

Table 2 presents statistics for the synchronization in the timing of price changes within a retail chain. Statistics in the first column are conditional on at least one price change in a store.[4] The frequency represents the percent of weeks in which the specific row occurred (averaged over goods and chains). The interpretation of the first row in the first column is conditional on at least one store within a retailer changing its price, more than one store belonging to that chain changed their price 69.2% of the time. Increasing the restriction that at least half of stores in the chain change their price has a negligible effect on the frequency. We see that, conditional on a price change, all stores in that chain change their price 42.9% of weeks. This is about a 25 percentage point reduction compared to the frequency for at least half of stores. However, much of this reduction can be accounted for by one store not changing its price.

The second and third columns of Table 2 serve as a check that these price changes are in the same direction. We see that requiring price changes to be in the same direction reduces the frequency of synchronized changes by about 10 percentage points across all specifications. Conditional on a price increase in one store, more than one store in the same chain increases its price 60.8% of the time. The frequencies for all stores in a chain

[4] I follow a similar procedure as Hee Hong et al. (2021) and Alvarez et al. (2016) in limiting a price change to be at least one cent and less the infinity. Recall, posted prices are not provided by the IRI, and instead I calculate price as $P_{ijt} = \frac{Rev_{ijt}}{Q_{ijt}}$. Thus, fractional price changes may occur due to this method. Eliminating infinite price changes further helps account for measurement error.

Table 2: Synchronization of Price Changes

	Any Change	Price Increases	Price Decreases
More than One Store	69.2%	60.8%	62.4%
At least Half of Stores	68.7%	54.1%	55.6%
All but One Store	56.4%	43.9%	44.9%
All Stores	42.9%	30.8%	32.1%

Note: This table presents statistics for the synchronization of price changes within a retail chain. All statistics are conditional on at least one price change in a store. The frequency represents the percent of weeks in which the specific row occurred (averaged over goods and chains). The interpretation of the first column in the last row is conditional on at least one store within a retailer changing its price, all stores belonging to that chain changed their price 43% of the time. The second and third columns document whether these price changes are in the same direction. Thus, conditional on a price increase/decrease within a chain, all stores change their price 30.8%/32.1% of the time.

increasing/decreasing their price in the same period are 30.8% and 32.1%, respectively. Differences in the conditional price increase and price decrease frequencies are less than 2 percentage points across all specifications.

3.2 Variance Decomposition

Table 2 suggests that retailers highly synchronize the timing of their price changes across stores. These price changes are also typically in the same direction. However, the statistics presented do not provide information on the magnitude of these price changes. Although all stores in a chain change their price in the same direction over 30% of the time, the size of price changes may vary significantly across stores. To account for this, I conduct a variance decomposition of store's relative prices. This variance decomposition also helps account for the feature shown in Figure 1 where individual stores are often a week early or late to update their price to the retail chain price which can bias the previous price change statistics downward.

I begin by modelling the log price ($p_{j,r,t}$) for store j belonging to retail chain r in week t as

$$p_{j,r,t} = \alpha_t + \delta_j + \gamma_{r,t} + \epsilon_{j,r,t} \tag{1}$$

where α_t is a week fixed effect, δ_j is a store fixed effect, $\gamma_{r,t}$ is a chain-by-week fixed effect, and $\epsilon_{j,r,t}$ is the residual. This equation is estimated separately for each good which eliminates the need to include a product component.[5] Using these estimated parameters, I perform the following variance decomposition for each good:

$$Var(p_{j,r,t} - \hat{\delta}_j) = Var(\hat{\alpha}_t) + Var(\hat{\gamma}_{r,t}) + Var(\hat{\epsilon}_{j,r,t}) \tag{2}$$

I normalize $p_{j,r,t}$ by $\hat{\delta}_j$, the average price in a store, in order to analyze price variation over time rather than constant differences in the average price across chains.[6] Thus, the total variance of the relative price is decomposed into three components: price changes that occur across all stores in the same week regardless of the retail chain ($\hat{\alpha}_t$), price changes that occur across all stores in the same week within a retail chain ($\hat{\gamma}_{r,t}$), and individual store-level price changes ($\hat{\epsilon}_{j,r,t}$).

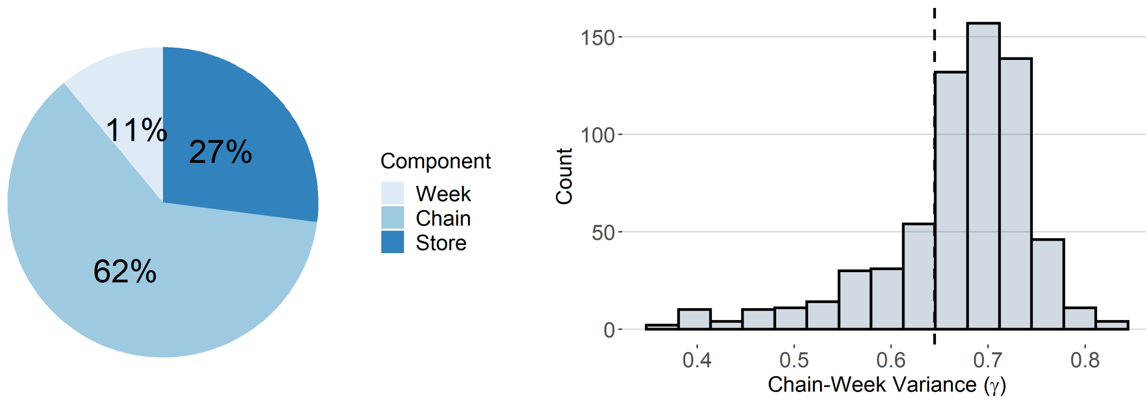
Panel (a) of Figure 2 presents the weighted averages from the variance decomposition. The week component α_t estimate of 11% suggests that price changes are not highly correlated across chains. However, the chain-week component $\gamma_{r,t}$ explains 62% of price variation on average. This suggests that price changes and their magnitude are highly correlated for stores within the same chain. Although the results suggest that individual store managers do maintain some flexibility when changing their price with the store component $\epsilon_{j,r,t}$ explaining about one quarter of relative price dispersion.

Panel (b) plots the distribution of the estimated chain component for all goods. The vertical dashed line represents the cutoff for the first quartile at 64.5%. The minimum variation explained by the chain-week component is 35.7%. Overall, the chain-week component can explain at least half of the price variation for about 625 out of the 655 goods that the

[5]Estimation follows a similar procedure used in Daruich and Kozlowski (2021) and Kaplan et al. (2016). See Appendix A.1.1 for more details.

[6]The variance decomposition for relative price variation over time and constant differences in the average price across chains need need not necessarily be the same. As detailed in Crucini and Telmer (2020), the decomposition for relative price variation over time is the relevant statistic for business cycle models such as the one in this paper.

Figure 2: Variance Decomposition



(a) Component Averages **(b)** Chain Component

Note: This figure presents the results of the variance decomposition in Equation (2). The variance decomposition is conducted separately for each good. Panel (a) presents the mean estimate for each component of the decomposition. Panel (b) plots the distribution of the chain-week variance (γ) over all goods. The vertical dashed line represents the cutoff for the first quartile.

decomposition was computed for.

Robustness Checks I perform several robustness checks of the above variance decomposition. First, I replace temporary sale prices with the previous regular/non-sale price. The behavior of temporary sale prices often behave differently than regular prices (Eichenbaum et al., 2011; Anderson et al., 2017). I follow the method in Eden et al. (2021) of defining a temporary sale price as a 10% drop in price followed by a price equal to or above the pre-sale price within four weeks.[7,8] Second, I estimate the variance decomposition using monthly rather than weekly prices.[9] Lastly, I perform the variance decomposition with the combination of these two restrictions.

The results of these robustness checks are presented in Appendix Figure A.2. Replacing temporary sale prices with the last observed regular/non-sale observation reduces the weighted average chain-week component by about 15 percentage points to 47%. Nearly all

[7] Limitations of the IRI sales indicator are privded in Eden et al. (2021).

[8] This definition is similar to others in the literature (Coibion et al., 2015; Nakamura and Steinsson, 2008).

[9] I follow Gagnon and López-Salido (2020) in selecting the weekly price observation that spans the 15th of the month to reflect BLS price sampling methods.

of this decline is a result of an increase in the idiosyncratic store component which is now 41.5%. Sampling monthly observations rather than weekly observations has negligible effects on the results for the analogous sale/non-sale price decompositions. In the weakest specification (monthly/non-sale prices), the chain-week component still accounts for at least half of relative price variation for 380 of the 655 goods. Loosening this restriction slightly to 40% of price variation returns the number of goods to a similar level as in the baseline specification, 624 out of 655.

4 Menu Cost Model with Retail Chains

This section analyzes a menu cost model extended to account for price synchronization within retail chains. I begin by documenting store-level pricing decisions in a standard menu cost model without retail chains as in Nakamura and Steinsson (2008).

4.1 Standard Model

Consider a firm (z) with real profits given by:

$$\Pi_t(z) = \frac{p_t(z)}{P_t}c_t(z) - \frac{W_t}{P_t}L_t(z) - K\frac{W_t}{P_t}I_t(z) \tag{3}$$

where P_t represents the aggregate price level. The first term $\frac{p_t(z)}{P_t}c_t(z)$ is the firm's revenue where $\frac{p_t(z)}{P_t}$ is the firm's relative price and $c_t(z)$ the firm's demand. The firm's total cost of producing in period t is the real wage $\frac{W_t}{P_t}$ multiplied by the quantity of labor demanded $L_t(z)$. The last term is the firm's menu cost as firm's must hire an additional K units of labor to change its price. $I_t(z)$ is an indicator variable that is equal to one if the retailer changes its price in period t and zero otherwise. Thus, the firm only pays the menu cost if they change their price.

Assume that the demand for the firm's good, $c_t(z)$, is proportional to its relative price:

$$c_t(z) = C\left(\frac{p_t(z)}{P_t}\right)^{-\theta} \tag{4}$$

where C is a constant which determines the size of the market. The firm produces its good using a linear technology:

$$y_t(z) = A_t(z)L_t(z) \tag{5}$$

where $y_t(z)$ denotes the output of the firm in period t and $A_t(z)$ denotes the productivity of the firm. Markets clear in equilibrium, so that $y_t(z) = c_t(z)$. Using equations (4) and (5), we have that $L_t(z) = c_t(z)/A_t(z)$.

Following Nakamura and Steinsson (2008), I assume that the real wage is constant and equal to $\frac{W_t}{P_t} = \frac{\theta-1}{\theta}$. Substituting the real wage, firm demand, and market clearing conditions into (3) yields

$$\Pi_t(z) = C\left(\frac{p_t(z)}{P_t}\right)^{-\theta}\left(\frac{p_t(z)}{P_t} - \frac{\theta-1}{\theta}\frac{1}{A_t(z)}\right) - K\frac{\theta-1}{\theta}I_t(z) \tag{6}$$

The firm then chooses its price at time t to maximize discounted profits:

$$V\left(p_{t-1}(z)/P_t, A_t(z)\right) = \max_{p_t(z)}[\Pi_t(z) + \beta E_t V\left(p_t(z)/P_{t+1}, A_{t+1}(z)\right)] \tag{7}$$

where $V(\cdot)$ is the firm's value function and β is the discount factor. The firm's state variables are its relative price p_{t-1}/P_t and productivity level $A_t(z)$ as evident from (6).

Uncertainty arises from aggregate shocks to the price level and idiosyncratic productivity shocks. The process for the price level follows:

$$\log P_t = \mu + \log P_{t-1} + \eta_t \tag{8}$$

where $\eta_t \sim N\left(0, \sigma_\eta^2\right)$. Productivity follows an AR(1) process:

$$\log A_t(z) = \rho \log A_{t-1}(z) + \epsilon_t(z) \tag{9}$$

where $\epsilon_t(z) \sim N\left(0, \sigma_\epsilon^2\right)$.

4.2 Retail Chain Extension

I extend the menu cost model to account for retail chain pricing by including a common retail component to the store's productivity process. Thus, in the extended model, a store z which belongs to retail chain r follows the productivity process:

$$\begin{aligned} \log A_t(z) &= \rho \log A_{t-1}(z) + \epsilon_t(z) && (10) \\ &= \rho \log A_{t-1}(z) + \varepsilon_t(r) + \varepsilon_t(z) && (11) \end{aligned}$$

where $\varepsilon_t(r) \sim N\left(0, \sigma_{\varepsilon_r}^2\right)$ and $\varepsilon_t(z) \sim N\left(0, \sigma_{\varepsilon_z}^2\right)$ are independent. Similarly, retail chain r has a productivity process that follows $\log A_t(r) = \rho \log A_{t-1}(r) + \varepsilon_t(r)$.

I also assume that the retailer sets the price of store $z \in r$ in period t with probability λ, and store z sets its optimal price with probability $1 - \lambda$. When determining store z's price, the retailer has the added restrictions that they (1) can set only one price for all stores belonging to r and (2) observe only chain-level state variables. The profit function of the retail chain can then be written as:

$$\Pi_t(r) = \sum_{z \in r} \left(C \left(\frac{p_t(r)}{P_t} \right)^{-\theta} \left(\frac{p_t(r)}{P_t} - \frac{\theta - 1}{\theta} \frac{1}{\hat{E}_t A_t(z)} \right) - K \frac{W_t}{P_t} I_t(r) \right) \tag{12}$$

where $\hat{E}_t$ denotes the chain's expectation operator. Using Equation (11), we have $\hat{E}_t A_t(z) = A_t(r)$.[10] These assumptions simplify the retailer's problem and allow the retailer to behave

[10]Recall that $A_t(z) = \rho A_{t-1}(z) + \epsilon_t(z)$. Consider the $MA(\infty)$ representation $A_t(z) = \sum_{i=0}^{\infty} \rho^i \epsilon_{t-i}(z) =$

similarly to an individual store with the following profit and value functions:

$$\Pi_t(r) = C\left(\frac{p_t(r)}{P_t}\right)^{-\theta}\left(\frac{p_t(r)}{P_t} - \frac{\theta-1}{\theta}\frac{1}{A_t(r)}\right) - K\frac{\theta-1}{\theta}I_t(r) \tag{13}$$

$$V\left(p_{t-1}(r)/P_t, A_t(r)\right) = \max_{p_t(r)}[\Pi_t(r) + \beta E_t V\left(p_t(r)/P_{t+1}, A_{t+1}(r)\right)] \tag{14}$$

4.3 Calibration

I calibrate the model to match four empirical moments separately for each of the 655 goods in the sample. These moments are the (1) mean fraction of adjusted prices, (2) mean absolute size of a (non-zero) price change, (3) the fraction of small price changes, and (4) the chain-week component of the variance decomposition in Section 3.[11] I match these moments using the menu cost (K/C), the volatility of the retailer's productivity shock (σ_{ε_r}), the volatility of the store's total productivity shock (σ_{ϵ_z}), and the probability that the retailer sets an individual store's price (λ).

Table 3 presents the set of calibrated parameters. Means are presented for the internally calibrated parameters which vary across goods. The mean estimated parameters are $K/C = 0.009, \sigma_{\varepsilon_r} = 0.03, \sigma_{\epsilon_z} = 0.048$, and $\lambda = 0.502$. The remaining parameters $(\beta, \theta, \mu, \sigma_\eta, \rho)$ are set similar to Nakamura and Steinsson (2008) or Nakamura and Steinsson (2010) and do not vary across goods. I set the discount factor to $\beta = 0.96^{1/12}$, the elasticity of demand to $\theta = 4$, the persistence of both retailer and store-level productivity to $\rho = 0.7$. The inflation process follows $\mu = 0.0022$ and $\sigma_\eta = 0.0028$.[12]

$\sum_{i=0}^{\infty} \rho^i[\varepsilon_{t-i}(r) + \varepsilon_{t-i}(z)]$. Separating the retail and store terms and taking expectations yields: $\hat{E}_t A_t(z) = \hat{E}_t[\sum_{i=0}^{\infty} \rho^i \varepsilon_{t-i}(r) + \sum_{i=0}^{\infty} \rho^i \varepsilon_{t-i}(z)] = A_t(r) + \sum_{i=0}^{\infty} \rho^i \hat{E}_t[\varepsilon_{t-i}(z)] = A_t(r)$.

[11] Using aggregate data, it is common to use the median fraction of adjusted prices and median size of price changes. The issues regarding the mean and median are less pronounced when using sector-level data. I follow Nakamura and Steinsson (2010) and Carvalho and Kryvtsov (2021) and use the mean for each good.

[12] The inflation parameters are not taken directly from Nakamura and Steinsson (2008), but rather I follow their procedure. I calibrate μ and σ_η using CPI data from 2001-2007 to correspond with the sample period in this paper.

Table 3: Benchmark Parameters

Internally Calibrated (Means)	
Menu Cost	$K/C = 0.0176$
Retailer Productivity Shock Std. Dev.	$\sigma_{\varepsilon_r} = 0.045$
Store Productivity Shock Std. Dev.	$\sigma_{\epsilon_z} = 0.072$
Probability Retailer sets Price	$\lambda = 0.502$
Remaining Parameters	
Discount Factor	$\beta = 0.96^{1/12}$
Elasticity of Demand	$\theta = 4$
Persistence of Productivity	$\rho = 0.7$
Mean Price Level Growth	$\mu = 0.0022$
Standard Deviation of Price Level Growth	$\sigma_\eta = 0.0028$

Note: This table presents the parameters used in the benchmark model. The menu cost, retailer productivity shock volatility, store-level productivity shock volatility, and probability that the retailer sets the store price are internally calibrated. The remaining parameters are set similar to either Nakamura and Steinsson (2008) or Nakamura and Steinsson (2010).

4.4 Model Intuition

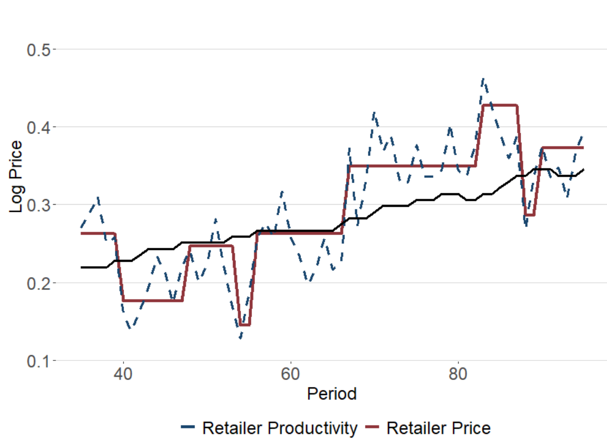
Although the retail pricing assumptions initially appear strong, they lend themselves to an intuitive interpretation of pricing. Pricing in this environment can be seen as (1) the retailer sets a target price for all stores belonging to its chain using chain-level state variables. This target price can reflect shocks to all stores in the chain such as warehousing/production costs. (2) Stores choose to keep the retail chain price or set their own price. Allowing stores to deviate from the retail-level price with probability $1 - \lambda$ serves as a reduced form modelling approach for the extra cost that a retailer needs to pay to observe idiosyncratic demand/supply shocks or the cost a store pays for deviating from the chain price.[13]

Figure 3 provides an example pricing path for a given retailer-store combination. Each panel corresponds to the same model sample period. The black line plots the aggregate price level in all three panels. Panel (a) plots the retailer's target price in red and its inverse

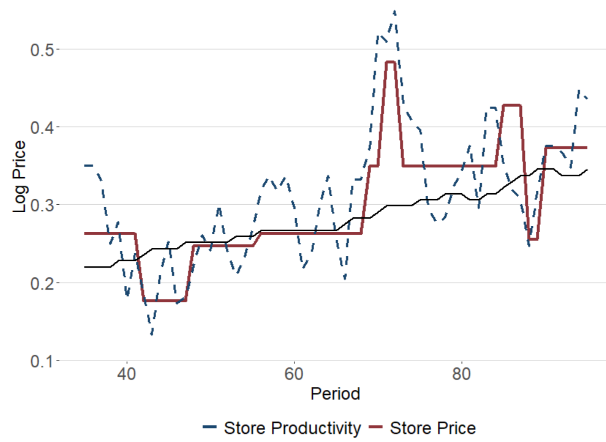
[13] I tested an alternative version of the model where stores pay a cost for deviating from the chain price. The model yielded similar pricing decisions.

Figure 3: Example Pricing Decision

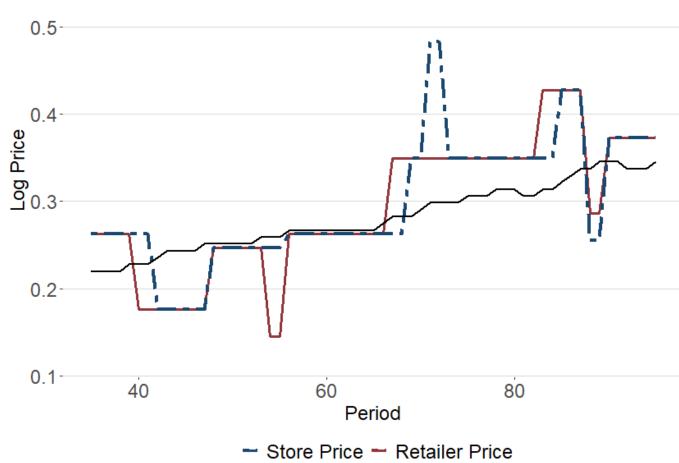
(a) Retail Price Path



(b) Store Price Path



(c) Store Deviations



Note: This figure presents a standard price path for both a retailer and a store. The black line plots the aggregate price level in both panels. Panel (a) plots the retailer's target price in red and its inverse productivity in blue. Panel (b) is analogous to panel (a) with observations at the store level. Panel (c) plots the retailer price in red and store-level deviations from the retailer price in blue.

productivity in blue. Corresponding with Step (1), we see that the retailer adjusts its price to account for both its productivity level and the aggregate price level.

Panel (b) plots the price path for an individual store belonging to the retailer in panel (a). Panel (c) helps highlight the main intuition of the model. The red line in panel (c) plots the retailer's price. The blue line highlights store-level deviations from the chain's price. The store sets its price at the chain-level price for most of the sample. Corresponding with

Step (2), we see that the store chooses a different price when its idiosyncratic productivity deviates enough from the chain's productivity. This is particularly evident in period seventy where the store's inverse productivity is much larger than the chain's productivity. Overall, the model does well in replicating price paths similar to the data where store deviations from the retail price occur infrequently. Furthermore, when deviations do occur they tend to coincide with periods in which the retail chain changes its price. The store then resets to the chain price within several periods similar to the price paths seen in Figure 1.

5 Selection Effects in Retail Chain Pricing

The previous sections have analyzed how retail chains are an important determinant in store-level pricing decisions. This section aims to relate the effect of uniform pricing within retail chain chains to the macroeconomy. Specifically, this section analyzes the selection effect—the concept that firms time their price changes optimally in response to aggregate shocks rather than change their prices at random. The first subsection briefly describes the intuition behind selection effects and the estimation procedure. The second subsection discusses the results.

5.1 Quantifying Selection Effects

To analyze how retail chains affect price selection, I simulate the calibrated retail chain model in Section 4. For each good, I compute the total number of chains in the IRI dataset as well as the average number of stores per chain rounded to the nearest whole number. The total number of stores in the simulation is then given by the total number of chains multiplied by the average number of stores per chain.[14] The same inflation process is drawn in each simulation for all 655 goods. The model is simulated for 300 periods with a burn-in sample of 100 periods for 400 periods in total.

[14]Given this calibration, the total number of stores may differ slightly in the model compared to the data. Overall, these differences tend to be small and are unlikely to affect the results.

After simulating the retail chain model, I perform a counterfactual analysis where stores do not adhere to the retail-chain constraint. Each store faces the same inflation process and analogous productivity process in the retail-chain simulation. Thus, differences between the models are not driven by different productivity draws and solely by every store selecting its unconstrained optimal price in each period.

5.1.1 Specification

After simulating each model, I perform the following regression for each good:

$$\Delta \log p_{jt} = \alpha + \beta_P \Delta \log P_t + \beta_A \Delta \log A_{jt} + \epsilon_{jt} \tag{15}$$

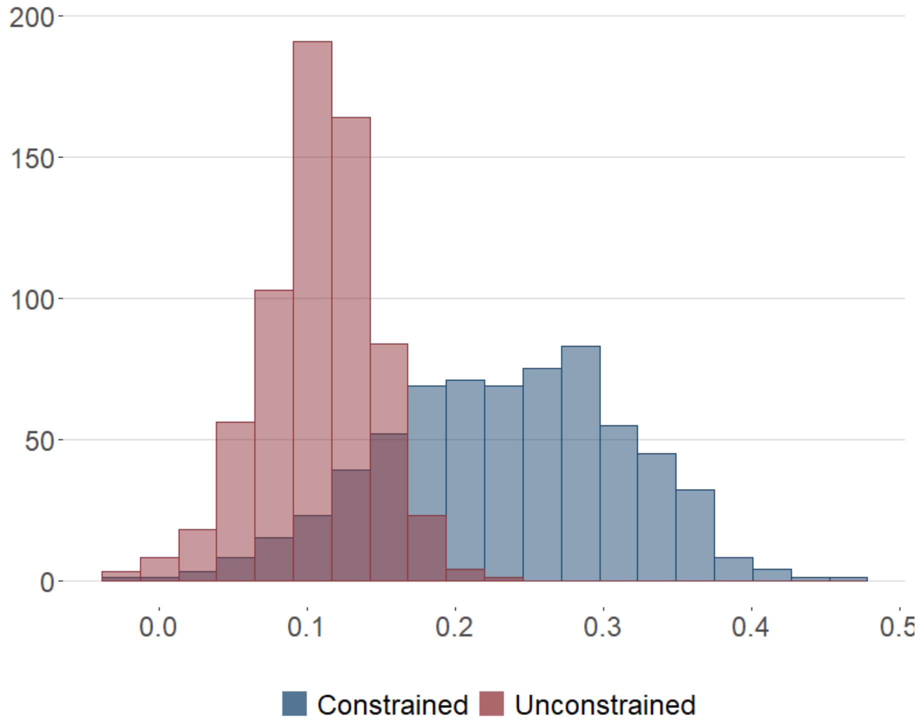
where $\Delta \log p_{jt}$ is the change of the store j's log price in period t, $\Delta \log P_t$ is the change of the log price level, and $\Delta \log A_{jt}$ is the change in the store's nominal cost.

In this circumstance, β_P represents my measure of the selection effect. As the specification is in logs, β_P represents the effect of a 1% increase in the aggregate price level on the store's price on average. For example, if $\beta_P = 0.2$, then a 1% increase in the aggregate price level leads to a 0.2% increase in a store's price on average.

5.1.2 Intuition

The specification in equation (15) lends itself to an intuitive interpretation of the selection effect. To see this, consider reducing the variance of the store's idiosyncratic productivity process in the standard menu cost model. Nakamura and Steinsson (2010) show reducing this variance leads nominal shocks to have less real effects on the economy. This is a result of the average inflation rate becoming a more important determinant in stores' pricing decisions. This is similar to the result in Golosov and Lucas (2007) who show in the absence of idiosyncratic shocks that their model converges to Caplin and Spulber (1987) in which nominal shocks have no real effects on the economy. In this setup, the coefficients β_P and

Figure 4: Selection Effects with Retail Chain Pricing



Note: This figure plots the distributions of β_P from equation (15) for the unconstrained model in red and the retail-chain model in blue. A KS-test suggests that the distribution are significantly different with a maximum difference of 0.75.

β_A can be loosely interpreted as the weight that a store places on the aggregate price level and its idiosyncratic productivity, respectively, when choosing to change its price. Thus, as β_P increases, stores place more weight on the aggregate price level when timing and deciding the size of their price changes. As a result, the real effects of nominal shocks would decrease.

5.2 Results

Figure 4 presents the results of equation (15). The bar graphs in red and blue plot the distribution of β_P over goods for the unconstrained and constrained retail-chain models, respectively. A KS-test suggests that the distributions are significantly different with a maximum distance of 0.75. The weighted mean β_P for the constrained and unconstrained models are 0.25 and 0.09, respectively. This difference suggests that the standard menu cost model without retail chains significantly underestimates the degree of selection. Consequently, this suggests the standard menu cost model overestimates the degree of monetary non-neutrality by not accounting for price synchronization within retail chains.

6 Conclusion

This paper examines selection effects in retail chain pricing. Using scanner-level data, I find that retail chains synchronize the timing and magnitude of their price changes across stores. A variance decomposition suggests that retail chains account for almost two-thirds of stores' relative price dispersion on average. This relationship is prevalant across almost all goods in my sample with the retail chain component of the decomposition accounting for at least half of price variation for 625 of the 655 goods. I develop a menu cost model with retail chain price synchronization to account for this finding. After calibrating the model separately for all 655 goods in my sample, I then measure selection by regressing the change in a store's log price on the change in the aggregate price level. My estimates suggest that a 1% increase in the aggregate price level leads to a 0.25% increase in a store's price on average. This effect is more than double suggested by an analogous simulation of the standard menu cost model without retail chains. This relationship suggests that the standard menu cost model overestimates the degree of monetary non-neutrality by ignoring synchronization in retail chain pricing.

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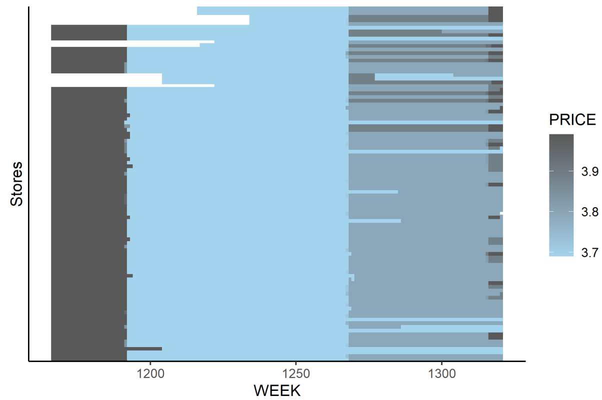
A Appendix

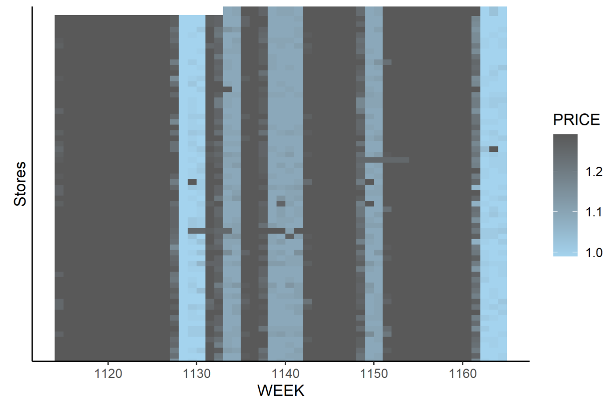
A.1 Empirics

Figure A.1: Retail Chain Price Synchronization

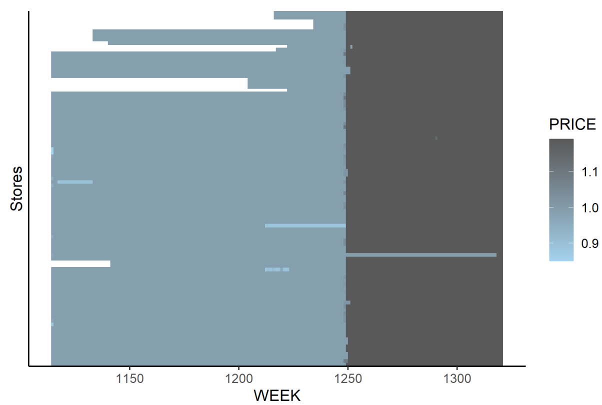
(a) Alternative Sugar Product



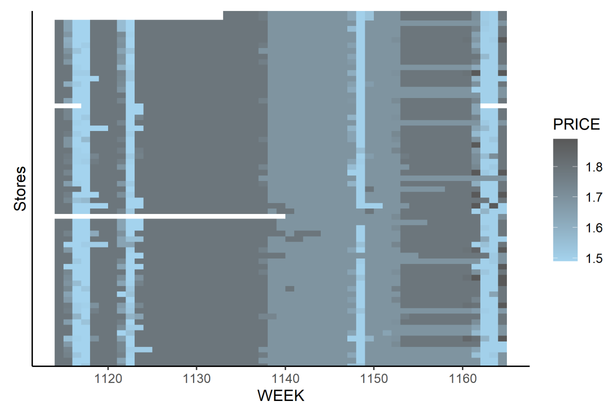
(b) Mustard Product



(c) Soup Product



(d) Facial Tissue Product



Note: This figure plots examples of uniform pricing within a retail chain. Each point on the y-axis represents an individual store belonging to the retail chain. Darker (lighter) shades represent higher (lower) prices. Missing values are represented by white space. Panel (a) presents an example for alternative sugar product compared to Figure 1. Panels (b), (c), and (d) present an example for a mustard, soup, and facial tissue product, respectively.

A.1.1 Variance Decomposition

The variance decomposition in Section 3 began by modelling prices as

$$p_{j,r,t} = \alpha_t + \delta_j + \gamma_{r,t} + \epsilon_{j,r,t} \tag{A.1}$$

where α_t was a week fixed effect, δ_j was a store fixed effect, $\gamma_{r,t}$ was a chain-by-week fixed effect, and $\epsilon_{j,r,t}$ was the residual. Due to the size of the dataset, I used the method of iterative means to estimate the fixed effects following Daruich and Kozlowski (2021) and Kaplan et al. (2016). The order of the estimation is (1) δ_j, (2) α_t, (3) $\gamma_{r,t}$, and (4) $\epsilon_{i,j,t}$. Thus, each fixed effect is estimated as (good index i is omitted as estimation is conducted separately for each good):

$$\hat{\delta}_j = \frac{1}{T_j} \sum_t p_{j,r,t} \qquad \text{Store Component} \tag{A.2}$$

$$\hat{\alpha}_t = \frac{1}{N_{j,t}} \sum_j \left(p_{j,r,t} - \hat{\delta}_j \right) \qquad \text{Week Component} \tag{A.3}$$

$$\hat{\gamma}_{r,t} = \frac{1}{N_{j \in r,t}} \sum_{j \in r,t} \left(p_{j,r,t} - \hat{\delta}_j - \hat{\alpha}_t \right) \qquad \text{Chain-Week Component} \tag{A.4}$$

$$\hat{\epsilon}_{j,r,t} = p_{j,r,t} - \hat{\delta}_j - \hat{\alpha}_t - \hat{\gamma}_{r,t} \qquad \text{Residual Component} \tag{A.5}$$

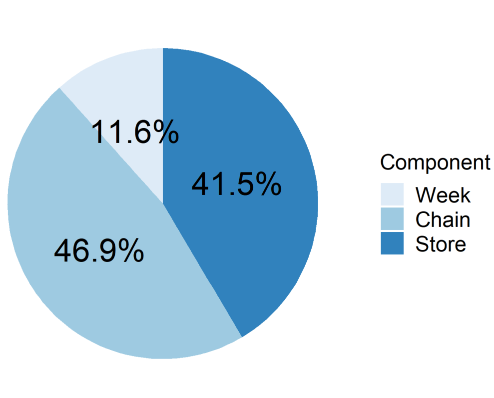
where T_j is the number of weeks that store j has a posted price, $N_{j,t}$ is the total number stores in week t, and $N_{j \in r,t}$ is the total number of store observations that belong to retail chain r in week t.

After estimating the fixed effects, the following variance decomposition of relative prices was performed $Var(p_{j,r,t} - \hat{\delta}_j) = Var(\hat{\alpha}_t) + Var(\hat{\gamma}_{r,t}) + Var(\hat{\epsilon}_{j,r,t})$. Several assumptions lead to the absence of covariance terms in this equation. First, $E[\alpha_t] = 0$. Thus, deviations from a store's average price are zero in expectation. Second, in a given week, deviations from a store's relative price are zero in expectation after accounting for the week component, $E[\gamma_{r,t}|t] = 0$.

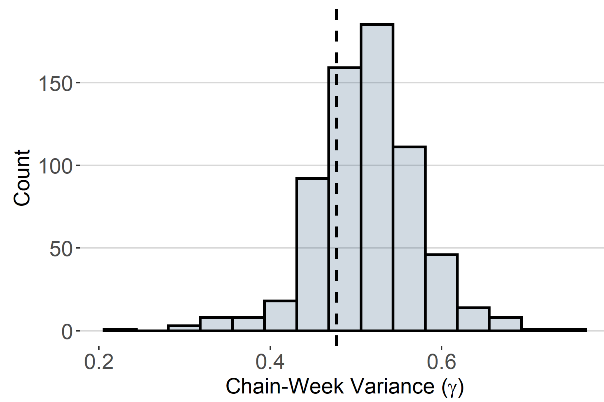
Figure A.2: Variance Decomposition (Robustness Checks)

Non-sale Observations

(a) Component Averages

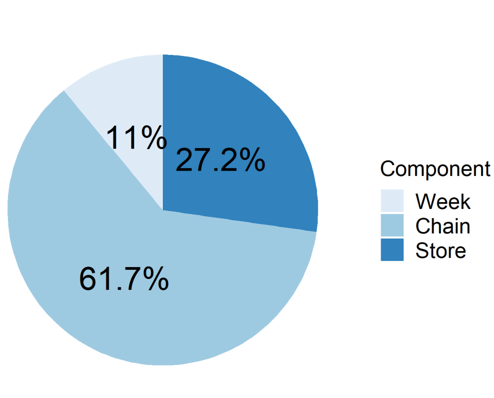


(b) Chain Component

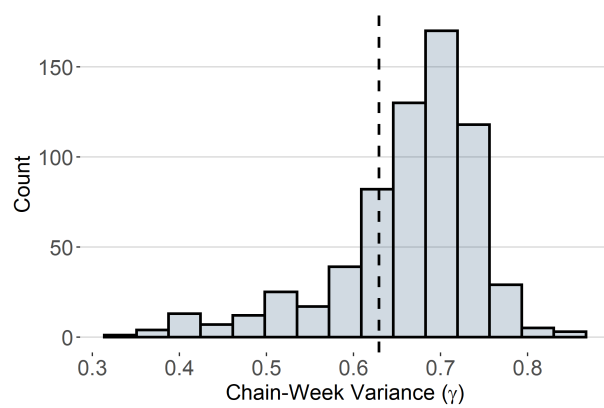


Monthly Observations

(c) Component Averages

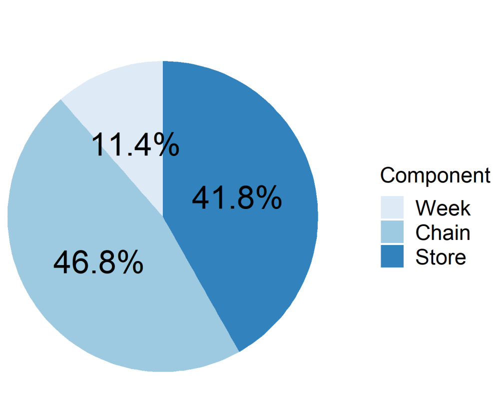


(d) Chain Component

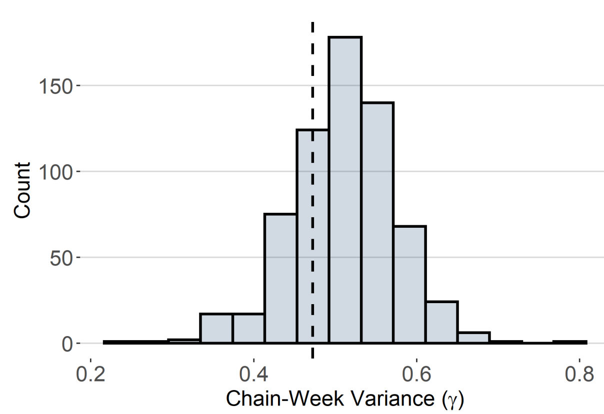


Monthly Non-sale Observations

(e) Component Averages



(f) Chain Component



Note: This figure presents the results of the variance decomposition in Equation (2). The variance decomposition is conducted separately for each good. Panel (a) presents the mean estimate for each component of the decomposition. Panel (b) plots the distribution of the chain-week variance (γ) over all goods. The vertical dashed line represents the cutoff for the first quartile.