Retail inventories and inflation dynamics: The price margin channel*

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Abstract

Using industry-level data and measures of supply conditions, we estimate the elasticity of retail price margins with respect to inventories along the retailer's optimal pricing curve. We find that this elasticity is negative and statistically significant, consistent with higher retail price margins when retailers face greater costs of holding finished-good inventories. We then assess the implications of this channel for inflation dynamics within a New Keynesian Phillips curve (NKPC) framework that links inventories to retailers' markup behavior. Incorporating the inventory-sales ratio into the NKPC markedly improves the model's empirical fit and helps account for two notable recent inflation episodes: the missing disinflation of 2009–2011 and the COVID-era surge.

Keywords: Inflation; inventories; supply disruptions; Phillips curve.

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"Retail markups in a number of sectors have seen material increases in what could be described as a price-price spiral, whereby final prices have risen by more than the increases in input prices. The compression of these markups as supply constraints ease, inventories rise, and demand cools could contribute to disinflationary pressures."

—Lael Brainard (January 2023)[1]

1 Introduction

The Phillips curve has been a key pillar of the literature on inflation and the business cycle. Nevertheless, its empirical versions to this date leave a lot of room for improvement in accounting for inflation dynamics. In particular, the COVID-era inflation surge that originated in the goods sector was not well captured by the standard Phillips curve models.

In this paper, we argue that inventories—specifically, retail inventories of finished goods—play a critical role in shaping inflation dynamics through their impact on retail prices.[2] While the standard New Keynesian Phillips curve (NKPC) abstracts from inventories, we show that retail inventory fluctuations offer a key missing link: they help explain why prices rose sharply during periods of supply disruption and low inventory availability.

Our approach begins with a stylized model of a retail firm that jointly chooses prices and inventory stocks in the face of supply disruptions. We show that transitory supply shocks shift the firm's stocking policy without directly affecting its pricing decision, thereby enabling identification of the optimal pricing curve using instruments for inventory disruptions.

Empirically, we estimate the elasticity of retail price margins with respect to inventories using industry-level panel data spanning January 2006 to June 2025. The estimated elasticity is negative and economically significant: tighter inventories are systematically associated with higher price margins, even after controlling for cost variables. Instrumenting

[1]Speech of Federal Reserve Vice Chair Brainard on January 19, 2023, available at https://www.federalreserve.gov/newsevents/speech/brainard20230119a.htm.

[2]Between 2007 and 2023, retail and wholesale trade margins made up 46.6% of the purchasers' value of consumer goods—nearly half of what consumers pay—underscoring their importance for goods inflation dynamics.

inventory changes with observed supply disruptions to identify the elasticity along the retailer's optimal pricing curve further reinforces this relationship, supporting the hypothesis that inventory scarcity contributes directly to retail price increases and providing evidence of state-dependent retail pricing.

To assess the macroeconomic implications of this inventory-pricing channel, we extend the stylized retail firm model into a New Keynesian framework. Retailers face both Rotemberg-style nominal rigidities and time-varying markups arising from two sources: a Kimball (1995) demand structure and deep habit formation *a la* Ravn et al. (2006). This setup yields two NKPC representations. The sales-based NKPC highlights how inflation is tied to future marginal costs and marginal sales benefits, but is difficult to estimate directly except in the special case without time-varying markups. The stock-based NKPC, in contrast, relates inflation to observable inventory-sales ratios and expected marginal cost growth, offering a tractable and empirically robust formulation. In particular, the inventory-sales ratio serves as a sufficient statistic for understanding inflationary pressures arising from the model's endogenous retail markup behavior.

Estimating the stock-based NKPC using macroeconomic data, we find that incorporating the retail inventory-sales ratio markedly improves the model's empirical fit compared to standard NKPC specifications. In particular, the stock-based NKPC helps account for two prominent recent inflation episodes—capturing both the missing disinflation of 2009–2011 and the COVID-era surge. The underlying intuition is that detrended inventory levels were tight in both periods, generating additional inflationary pressures that bring model-implied inflation closer to the observed data. Because changes in the inventory-sales ratio orthogonal to movements in the expected marginal cost growth should reflect movements in retail sector markups within our model, the results highlight the important role that retail price markups may play in driving inflation dynamics.

Related literature. The COVID-era surge in inflation has sparked renewed interest in the role of supply-side disruptions in driving price dynamics. A growing literature documents how production and transportation frictions contributed to rising costs across sectors (Alessandria et al., 2023; Boehm and Pandalai-Nayar, 2022; Comin et al., 2023; Ferrante et al., 2023; Ortiz, 2022). These studies emphasize upstream channels—such as global supply chain bottlenecks, convex production technologies, and sectoral reallocation—as key drivers of inflationary pressures. We build on this line of research by focusing on a downstream margin that has received comparatively less attention: the pricing behavior of retailers facing inventory shortages. While prior work highlights how supply disruptions raise production costs, our contribution is to show that they can also amplify retail price margins when firms are constrained by limited inventory availability. A paper closely related to our topic is Cavallo and Kryvtsov (2023), which uses online micro-level stockout data to study the inflationary effects of consumer product shortages during the pandemic. We complement their analysis by leveraging industry-level panel data, which offers two distinct advantages. First, our data encompasses a broader set of retailers, including the motor vehicle dealer industry—a key contributor to goods inflation in the early stages of the pandemic. Second, we use retail gross margin data—the difference between the sales price and the acquisition cost—rather than retail prices, and we control for several industry-level cost measures, such as average hourly earnings. This allows us to analyze retailers' pricing behavior beyond what can be attributed to underlying cost pressures during this period.

The relationship between inventories and inflation has been explored in several studies, particularly in the context of business cycle models. Jung and Yun (2005), Lubik and Teo (2012), and Kryvtsov and Midrigan (2010, 2013) examine how inventory dynamics interact with pricing, often within frameworks that assume constant elasticity of substitution (CES) in demand. These papers typically find either a limited role for inventories in explaining inflation dynamics or a need for additional mechanisms—such as time-varying, countercyclical markups—to reconcile theory with the data, especially in response to monetary policy shocks. Our empirical analysis using industry-level data confirms that retail price margins respond in ways that are inconsistent with CES demand, supporting the need for richer pricing structures. In contrast to the prior literature, our model explicitly incorporates standard features that generate time-varying price markups, including habit formation and Kimball-style demand. We derive a representation of the NKPC in which the inventory-sales ratio serves as a sufficient statistic for retail markups. This approach allows us to empirically assess the role of time-varying markups in inflation dynamics without relying on direct and often noisy measures of price margins.

Our paper also contributes to the empirical Phillips curve literature, which has grappled with the declining explanatory power of traditional NKPC specifications in recent decades (Mavroeidis et al., 2014; Stock and Watson, 2020; Coibion and Gorodnichenko, 2025). A central debate in this literature concerns the inclusion of forward-looking variables that capture the information and beliefs shaping firms' pricing decisions. For example, Coibion and Gorodnichenko (2015) show that replacing professional inflation forecasts with household survey expectations can help resolve the 2009–2011 missing disinflation puzzle, highlighting the value of expectation measures that better reflect firms' information set. Reis (2023) similarly argues for combining multiple indicators of inflation expectations to obtain early and more accurate signals of inflation dynamics. In this spirit, we propose the inventory-sales ratio as a complementary forward-looking variable that reflects firms' near-term beliefs and strategic pricing behavior. Incorporating this measure directly into the NKPC significantly improves its empirical fit, allowing it to account for key episodes such as the 2009–2011 missing disinflation and the surge in goods inflation following the COVID-era supply disruptions.

The remainder of the paper is organized as follows. Section 2 presents a stylized retail firm model that motivates our identification strategy for estimating the inventory stock elasticity of the retail price margin. Section 3 implements this strategy using industry-level panel data. Section 4 extends the stylized model and derives a NKPC with inventories that is consistent with the empirically observed negative inventory elasticity of retail markups. Section 5 estimates the inventory-augmented Phillips curve to quantify the macroeconomic importance of retail pricing behavior, as reflected in the inventory-sales ratio. Section 6 concludes.

2 A stylized retail firm model

In this section, we present a stylized model of a retail firm to illustrate how temporary supply disruptions can be used to identify the firm's optimal pricing curve as a function of its inventory stock. The key insight is that while the firm's optimal *stocking* decision depends on both current and expected future costs of acquiring goods, its *pricing* decision depends only on the expected future cost. Therefore, changes in the current cost of acquiring goods—so long as they do not affect expectations of future costs—will shift the firm's stocking curve but leave its pricing curve unchanged. If supply disruptions are perceived to be transitory relative to other cost shocks, they can serve as valid instruments to trace out the firm's pricing curve. We first show this identification logic in a static one-period model, and then extend the insight to a dynamic two-period setting that makes explicit the role of intertemporal inventory decisions in separating pricing from stocking behavior.

2.1 One-period model

To build intuition about the retail firms' joint decisions over stocking and pricing, we consider a one-period model in which the firm purchases a stock of finished goods and sets a price at which to sell them. The firm simultaneously chooses the stock level and the selling price, taking as given the demand function and the unit cost of stocking. Demand for the good, denoted s, is given as $s = \boldsymbol{s}(a,p)$ where a is the stock and p is the price.[3] We assume the demand function satisfies $\partial \boldsymbol{s}/\partial a > 0$, $\partial^2 \boldsymbol{s}/\partial a^2 < 0$, and $\partial \boldsymbol{s}/\partial p < 0$. The first two conditions are standard in the inventory literature. For example, in stockout avoidance models, an additional unit of stock raises sales up to the point where stockouts are eliminated; in stock-elastic demand models, sales increase with an additional unit of stock but at a diminishing rate.

After sales, the firm may liquidate unsold inventory, $a - s$, incurring a cost. The total cost of stocking, net of liquidation, is given by:

$$(c + \xi)a - (1 - \gamma)c(a - s),$$

where c is the unit cost of stocking, ξ captures an additional shadow cost faced by the retailer (e.g., supply disruptions not embedded in c), and γ governs the liquidation cost. The parameter ξ is a stand-in for the difficulty in stocking by the retail firm not captured in the unit cost of stocking c.

[3] For simplicity, we normalize aggregate demand to 1.

The firm's profit is given by:

$$\phi = p\boldsymbol{s}(a,p) - (c+\xi)a + (1-\gamma)c(a - \boldsymbol{s}(a,p)).$$

The firm chooses a and p to maximize this profit.

The first order condition with respect to a (stocking) is:

$$p\frac{\partial \boldsymbol{s}}{\partial a} - (c+\xi) + (1-\gamma)c\left(1 - \frac{\partial \boldsymbol{s}}{\partial a}\right) = 0,$$

which simplifies to:

$$(p - (1-\gamma)c)\frac{\partial \boldsymbol{s}}{\partial a} = \gamma c + \xi. \tag{1}$$

Absent both a shadow cost of stocking ($\xi = 0$) and a liquidation cost ($\gamma = 0$), the right-hand side of (1) becomes zero. In that case, as long as $p > (1-\gamma)c$, the firm would optimally stock an infinite quantity ($a \to \infty$), driving $\partial \boldsymbol{s}/\partial a \to 0$. Therefore, at least one of ξ or γ must be strictly positive to yield a finite interior solution. The resulting stocking curve determines the optimal level of the stock as a function of the price, conditional on the cost parameters c, ξ, and γ.

The first order condition with respect to price is:

$$s = -(p - (1-\gamma)c)\frac{\partial \boldsymbol{s}}{\partial p}. \tag{2}$$

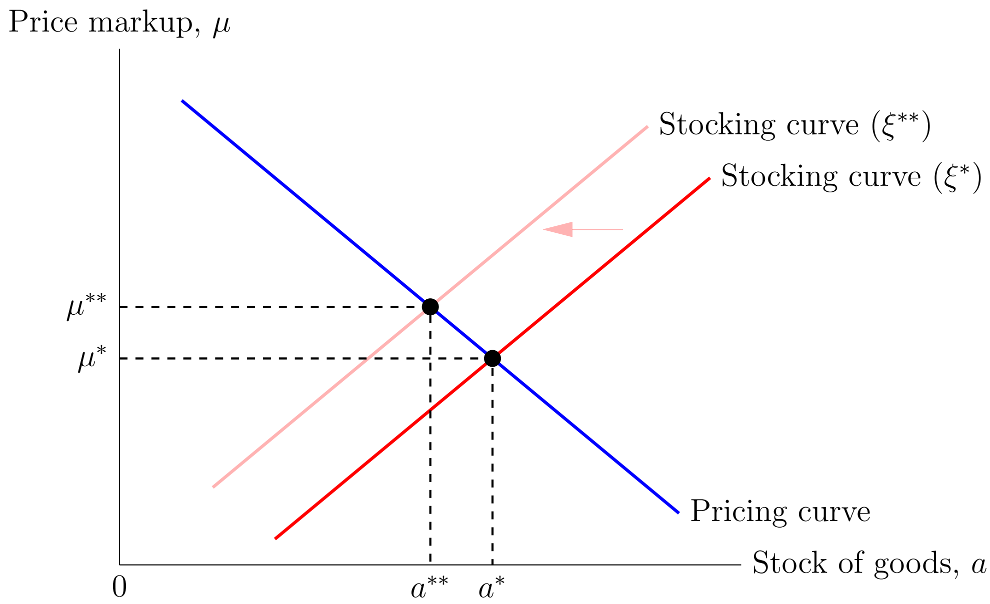
This pricing equation pins down the optimal price as a function of the level of the stock, taking c and γ as given. For example, suppose the demand function has constant price elasticity:

$$\boldsymbol{s}(a,p) = u(a) \times p^{-\eta},$$

where $u(a)$ is increasing in a and $\eta > 1$. Then the price markup is constant and given by:

$$\mu \equiv \frac{p}{(1-\gamma)c} = \frac{\eta}{\eta - 1},$$

Figure 1: Illustration of a Retailer's Equilibrium



Notes: This plot is illustrative. A finished-goods inventory model with a negatively sloped stocking curve would yield qualitatively similar implications.

which is the standard result under CES demand. In this case, the pricing curve is flat, and changes in the stock have no effect on the markup.

Taken together, the optimal stocking and pricing curves jointly determine the firm's equilibrium stock and price (or markup). A key feature of this simple model is that the shadow cost ξ appears only in the stocking condition—not in the pricing condition. As a result, shifts in ξ move the stocking curve without affecting the pricing curve, allowing us to trace out the firm's pricing behavior. Figure 1 illustrates this identification strategy. When $\xi = \xi^*$, the firm's equilibrium stock and markup are (a^*, μ^*). When ξ increases to $\xi^{**} > \xi^*$, the equilibrium shifts to (a^{**}, μ^{**}). Supply disruptions that affect ξ not captured by c therefore serve as valid instruments to recover the pricing curve. If the pricing curve is flat—as in the case of constant price elasticity—then changes in ξ would shift the stock without altering the markup. In contrast, if the pricing curve is downward sloping, as shown in the figure, then a higher ξ leads to lower stock and a higher markup. Verifying this inverse relationship between inventory and price margins is the focus of the empirical analysis that follows.

2.2 Two-period model

We now extend the logic of the one-period model to a dynamic, two-period setting in which inventories can be carried across periods. This extension verifies that the identification strategy remains valid when the firm makes intertemporal stocking decisions.

Assume the retail firm lives for two periods, facing the same demand function in each period as in the one-period model, $s = \boldsymbol{s}(a, p)$. In the first period, the firm purchases a stock of goods a_1, sets a price p_1, and sells $s_1 = \boldsymbol{s}(a_1, p_1)$. The remaining inventory $a_1 - s_1$ is carried over to the second period, subject to a depreciation rate δ. In the second period, the firm purchases n additional units, bringing the total available stock to:

$$a_2 = (1 - \delta)(a_1 - s_1) + n.$$

It then sets price p_2 and sells $s_2 = \boldsymbol{s}(a_2, p_2)$ units. As in the one-period model, leftover inventory at the end of the second period is liquidated at cost, governed by the parameter γ.

The firm maximizes the sum of discounted profits:

$$\pi = p_1 s_1 - (c_1 + \xi_1)a_1 + \beta\mathbb{E}_1 \left[p_2 s_2 - c_2(a_2 - (1 - \delta)(a_1 - s_1)) + (1 - \gamma)c_2(a_2 - s_2)\right],$$

where β is the discount factor, and $\mathbb{E}_1$ denotes expectations conditional on information available in period 1. We assume that the second-period supply disruption ξ_2 is unanticipated, so $\mathbb{E}_1\xi_2 = 0$.

The first-order condition with respect to a_1 (initial stocking) is:

$$(p_1 - \beta(1 - \delta)\mathbb{E}_1 c_2) \frac{\partial \boldsymbol{s}(a_1, p_1)}{\partial a_1} = c_1 + \xi_1 - \beta(1 - \delta)\mathbb{E}_1 c_2,$$

which mirrors the one-period stocking condition in equation (1).

Similarly, the first-order condition with respect to p_1 is:

$$s_1 = -\left(p_1 - \beta(1-\delta)\mathbb{E}_1 c_2\right) \frac{\partial \boldsymbol{s}(a_1, p_1)}{\partial p_1},$$

which corresponds to the pricing condition in equation (2).

As in the one-period case, the shadow cost ξ_1 enters only the stocking equation and not the pricing equation. This separation confirms that temporary supply disruptions—captured by changes in ξ_1—remain valid instruments for identifying the slope of the pricing curve in a dynamic environment.

2.3 Empirical proxy for the stock of goods: Inventory-sales ratio

In the next section, we turn to the data and implement this identification strategy using industry-level panel data to estimate the elasticity of retail price margins with respect to the stock of goods. In empirical work, we proxy the stock using the end-of-period inventories. Indeed, our stylized model implies a tight relationship between the stock of goods, a, and end-of-period inventories, inv, as given by:

$$inv = a - s.$$

Letting $is = inv/s$ denote the inventory-sales ratio and $\overline{IS}$ its long-run average, we obtain the following log-linear approximation:

$$\hat{a} = \hat{s} + \frac{\overline{IS}}{\overline{IS} + 1}\widehat{is},$$

where hatted variables denote log-deviations from their respective averages. This expression implies that changes in the stock-sales ratio and the inventory-sales ratio are proportionally related. As such, conditional on sales, fluctuations in the stock of goods are directly reflected in movements of the inventory-sales ratio. Accordingly, we use the inventory-sales ratio as an empirical proxy for the stock of goods in our model—controlling for sales—as it conveys equivalent information about stock dynamics and is both directly observable and widely used in the empirical literature.

3 Inventories and prices at the industry level

In this section, we use industry-level panel data to estimate how the retail and wholesale margin price reacts to changes in the inventory stock.[4]

3.1 Industry data

Our data set comprises monthly variables for eight industries in the retail and wholesale trade sectors, which we collectively refer to as the retail sector for simplicity, spanning from March 2006 to June 2025. From the Bureau of Labor Statistics (BLS), we collect industry-specific Producer Price Index (PPI) data, average hourly earnings, and total hours worked. Note that in the trade sectors, the PPI reflects gross margins—that is, the difference between the sales price and the acquisition cost of goods sold by retailers. From the Bureau of Economic Analysis (BEA), we incorporate information on real inventories and real sales, which are specifically sourced from the National Income and Product Accounts tables. We merge the BLS and BEA data at the three-digit North American Industry Classification System (NAICS) level, which represents the most granular classification available across these data sets. Table 1 presents the summary statistics for each variable and lists the retail industries included in our analysis.

3.2 Industry-level regression framework

To formally examine the relationship between inventory holdings and changes in the industry gross margin, we estimate the following regression,

$$\Delta_k \log(PPI_{i,t}) = \beta \Delta_k \log(IS_{i,t}) + \text{controls} + \delta + \delta_i + \delta_t + \eta_i t + \varepsilon_{i,t}, \tag{3}$$

where Δ_k denotes the k-th difference operator. The outcome variable is the change in the gross margin, measured as the log-difference in the PPI, from period $t-k$ to t. The coefficient of interest, β, captures the association between changes in the inventory-sales

[4] Since both retailers and wholesalers primarily manage finished-good inventories and typically do not transform the products as manufacturers do, we also include data from the wholesale trade industry for completeness of our analysis.

Table 1: Summary Statistics and Industry Names

Panel A: Summary Statistics	Mean	Median	Std.
Three-month percent change			
Inventory-sales ratio	-0.238	-0.203	3.453
PPI (gross margin)	-0.797	0.653	3.578
Average hourly earnings	0.674	0.622	1.515
Real sales	0.826	0.795	2.876
Hours worked	0.007	0.123	1.940
Manufacturing PPI	0.093	0.072	0.216
Six-month percent change			
Inventory-sales ratio	-0.446	-0.382	4.475
PPI (gross margin)	1.531	1.328	4.002
Average hourly earnings	1.360	1.268	1.743
Real sales	1.605	1.535	3.830
Hours worked	-0.066	0.264	2.720
Manufacturing PPI	0.188	0.134	0.360

Panel B: Industry Names	
Industry	NAICS code
Merchant wholesalers, durable goods	423
Merchant wholesalers, nondurable goods	424
Motor vehicle & parts dealers	441
Building materials & garden equipment & supply dealers	444
Food and beverage stores	445
Furniture, home furnishings, electronics, & appliance retailers	449
General merchandise stores	455
Clothing & clothing accessories retailers	458

Notes: Summary statistics are based on monthly data for the sample period spanning January 2005 to June 2025. Data are winsorized at top and bottom 0.5% of the empirical distribution. Industry classifications follow NAICS 2022 definitions.

ratio and changes in the gross margin. The control variables consist of the k-period log-differences of industry-level variables, including real sales, average hourly earnings, total hours worked, and a constructed measure of the PPI of upstream manufacturing suppliers. The upstream PPI for each retail industry is defined as:

$$PPI_{i,t}^{\text{upstream}} = \sum_j \frac{s_{ij,t_0}}{s_{i,t_0}} \times PPI_{j,t}, \tag{4}$$

where $PPI_{j,t}$ denotes the PPI of manufacturing industry j in period t, and s_{ij,t_0} is the value of inputs purchased by retail industry i from manufacturing industry j in the base year t_0.[5] The denominator, $s_{i,t_0} \equiv \sum_j s_{ij,t_0}$, represents the total value of manufacturing inputs used by industry i. The term $s_{ij,t_0}/s_{i,t_0}$ thus reflects the input share sourced from manufacturing industry j within industry i's manufacturing input bundle. Finally, the regression specification includes a constant (δ), industry fixed effects (δ_i) to control for time-invariant industry characteristics, time fixed effects (δ_t) to account for common shocks across all industries, and industry-specific linear time trends ($\eta_i t$) to absorb gradual, industry-specific trends over time.

3.3 Instrumental variables approach

Because stocking and pricing decisions are jointly determined, we seek to establish causality by instrumenting for the retailer's inventory-sales ratio. To this end, we construct three instruments that exploit plausibly exogenous variation in upstream suppliers' ability to deliver finished-goods inventories to downstream retailers.

From the retailer's perspective, such delivery disruptions may arise from (i) delays in the shipment of manufactured goods or (ii) disruptions in the manufacturing process itself, including suppliers' difficulties in sourcing raw materials. Our instruments are designed to capture both channels by measuring retailers' exposure to shocks that affect upstream manufacturers' capacity to produce and deliver goods.

Our three instruments take the form of shift-share variables, defined as:

$$Z_{i,t} = \sum_j \frac{s_{ij,t_0}}{s_{i,t_0}} \times \Delta_k Z_{j,t}, \tag{5}$$

where $\Delta_k Z_{j,t}$ represents a shift variable associated with manufacturer j. The three instruments described below differ in how the shift term $\Delta_k Z_{j,t}$ is defined.

Across all three instruments, the key identifying assumption is that, conditional on demand controls, the shift variables we define capture supply-side shocks. When mapped onto downstream industries via input-output weights, these shocks are assumed to affect

[5] We calibrate s_{ij,t_0} using data from the BEA Industry Input-Output Use Table, with $t_0 = 2007$, which is near the start of our sample period.

retail inventory behavior solely through supply chain linkages between retailers and manufacturers, and not through channels correlated with unobserved downstream demand or pricing shocks. Put differently, identification in our setting relies on plausibly exogenous shifts (Borusyak et al., 2025).

3.3.1 Global supply chain pressure index

Our first instrument is based on the Global Supply Chain Pressure Index (GSCPI), developed by staff at the Federal Reserve Bank of New York (Benigno et al., 2022). The GSCPI attempts to provide a comprehensive summary of potential global supply chain disruptions and is available from 1997 onward. Because the index is constructed at the aggregate level, we use lagged import shares across manufacturing industries to construct a shift variable at the industry level. Identification thus relies on plausibly exogenous shifts in manufacturers' supply driven by their differential exposure to global supply chain disruptions via import intensity.

The shift variable is defined as:

$$\Delta_k Z_{j,t}^{GSCPI} = m_{j,2007} \times \sum_{\ell=0}^{k} \varepsilon_{t-\ell}^{GSCPI}, \tag{6}$$

where $m_{j,2007}$ denotes the import exposure of manufacturing industry j in 2007. Import exposure is measured as the share of imported intermediate inputs in the industry's total intermediate input use.[6] We define ε_t^{GSCPI} as the residual from a regression of the log of the GSCPI on its lag, along with contemporaneous and lagged values of demand-driven core inflation (Shapiro, Forthcoming). We residualize the GSCPI in this way to isolate the supply-driven component of the index, as it may also reflect demand-side fluctuations (Bai et al., 2024). In the first stage, the GSCPI-based shift-share instrument is negatively correlated with retailers' inventory holdings.

[6] The data come from the 2007 BEA input-output tables. Imports of intermediate inputs are taken from the import matrix, while total intermediate input use is taken from the use table.

3.3.2 Bai et al. (2024)'s supply chain disruption index

We next consider an alternative instrument for global supply disruptions based on the Average Congestion Rate (ACR) index of Bai et al. (2024), available from January 2017 to June 2024. The ACR index measures global port congestion and is regarded as an exogenous indicator of shipping disruptions. Manufacturers that rely more heavily on imported inputs are likely to be more exposed to such disruptions; accordingly, we again use lagged import shares to capture industry-level exposure.

The corresponding shift variable is constructed as:

$$\Delta_k Z_{j,t}^{ACR} = m_{j,2007} \times \sum_{\ell=0}^{k} \varepsilon_{t-\ell}^{ACR}, \tag{7}$$

where ε_t^{ACR} is the residual from a regression of the ACR index on its own lag.[7] In the first stage, the ACR-based shift-share instrument is negatively correlated with retailers' inventory holdings.

3.3.3 Supply shock based on capacity utilization

The two shift-share instruments described above are based on global supply chain disruptions. At the same time, there is potentially useful identifying variation in domestic supply disruptions.

To capture this, we construct a third instrument using industry-specific capacity utilization rates estimated by the Federal Reserve, defined as the ratio of an output index to a capacity index.[8] In constructing the capacity index, inputs are assumed to be sufficiently available to operate existing capital. Therefore, when temporary supply disruptions constrain input availability, output declines while capacity remains unchanged, resulting in a lower capacity utilization rate.

Analogous to the global instruments, we isolate supply-driven variation in capacity utilization by purging current and lagged demand factors. To further ensure that the identified

[7] We regress the ACR index only on its own lag, as we already treat the series as orthogonal to demand-driven disturbances.

[8] See https://www.federalreserve.gov/releases/g17/CapNotes.htm for details.

shock reflects unexpected disruptions rather than predicted trends, we also purge lagged values of capacity utilization.

The capacity utilization-based shift-share instrument is defined as:

$$\Delta_k Z_{j,t}^{CU} = \sum_{\ell=0}^{k} \varepsilon_{j,t-\ell}^{CU}, \tag{8}$$

where ε_{jt}^{CU} denotes the residualized capacity utilization rate for upstream industry j.

In the first stage, the capacity utilization-based shift-share instrument is positively correlated with retailer inventories. This comovement implies that supply disruptions, which lower upstream capacity utilization, are associated with reductions in downstream inventory holdings. Below, we discuss how this instrument relates to recent work on capacity utilization and supply chain bottlenecks.

3.4 Regression results

We begin by estimating equation (3) using Ordinary Least Squares (OLS). The results are reported in the OLS column of Table 2. Panels A and B present estimates for the three-month difference ($k = 3$) and the six-month difference ($k = 6$), respectively. In both cases, changes in the inventory-sales ratio are negatively correlated with the retailer's gross margin, although the coefficient is statistically significant at the 1 percent level only for the six-month horizon. Specifically, a one percentage point decline in the inventory-sales ratio over six months is associated with a 0.18 percentage point increase in the gross margin over the same period.

Next, we implement our instrumental variables (IV) strategy using our three instruments, introduced individually and one at a time. The IV estimates are reported in the final three columns of Table 2. Across both horizons ($k = 3$ and $k = 6$), a one percentage point decline in the inventory-sales ratio leads to a statistically significant increase in the retail gross margin. The estimated elasticities range from approximately -0.47 to -0.89.

The first-stage F-statistics are near or exceed the conventional threshold of 10 in most cases, indicating that the instruments are sufficiently strong. In addition, the Anderson-Rubin Wald F-test p-values are consistently below 5 percent, lending further support to

Table 2: Industry Regression Results

	OLS	IV		
	PPI	GSCPI	ACR	CU
Panel A: Three-Month Difference ($k = 3$)				
IS ratio	-0.089	-0.644**	-0.785**	-0.625***
	(0.085)	(0.288)	(0.332)	(0.240)
First-stage F-stat		7.59	5.97	25.89
AR Wald F p-value		0.042	0.048	0.010
Observations	1615	1607	646	1607
Sample	2005m1–2025m6	2005m1–2025m6	2017m1–2024m6	2005m1–2025m6
Panel B: Six-Month Difference ($k = 6$)				
IS ratio	-0.180***	-0.458***	-0.602***	-0.471***
	(0.066)	(0.166)	(0.157)	(0.173)
First-stage F-stat		15.27	16.60	19.32
AR Wald F p-value		0.038	0.019	0.010
Observations	1591	1583	643	1583
Sample	2005m1–2025m6	2005m1–2025m6	2017m1–2024m6	2005m1–2025m6

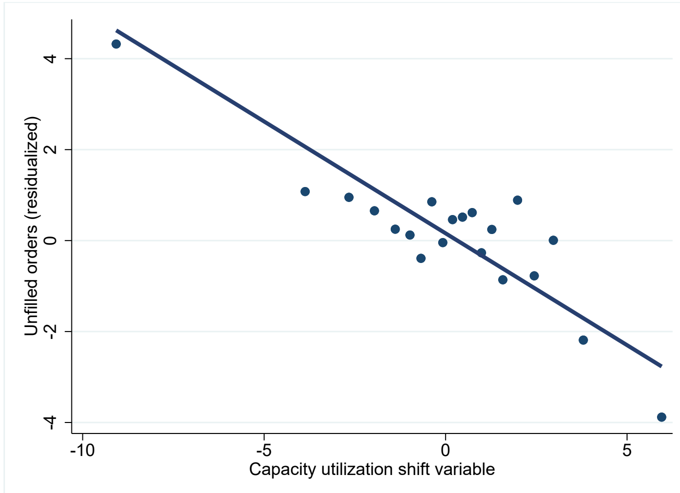
Notes: Driscoll–Kraay standard errors are reported in parentheses. Instruments for the IV columns are: Global Supply Chain Pressure Index (GSCPI), Average Congestion Rate (ACR), and upstream capacity utilization shocks (CU). * p<0.10, ** p<0.05, *** p<0.01.

the validity of our inference, especially in the presence of potentially weak instruments.

Relative to OLS, the IV estimates are more negative, suggesting that the OLS estimates are biased upward. This pattern is consistent with the mechanism illustrated in Figure 1, where an upward shift in the pricing curve results in higher margins and greater inventory stocks. In this case, the OLS estimate fails to account for unobserved movements in the pricing curve, thereby inducing a positive correlation between the inventory-sales ratio and the gross margin, and leading to an upward bias in the OLS coefficient.

In the Appendix, we show that these results are robust to including additional non-labor cost controls, using a shorter-sample data set from the BLS satellite inputs to industry price indexes.

Figure 2: Unfilled Orders and Capacity Utilization



Notes: The figure displays a binned scatter plot of three-month changes in unfilled orders against the capacity utilization-based shift variable. Unfilled orders are residualized with respect to contemporaneous new orders.

3.5 Relation with the recent literature on capacity utilization

To corroborate the interpretation that greater supply disruptions reduce capacity utilization in the data, we examine the relationship between our capacity utilization-based shift variable, defined in equation (8), and industry-level manufacturers' unfilled orders. To control for demand conditions, we residualize unfilled orders with respect to contemporaneous new orders. Figure 2 presents a binned scatter plot of residualized unfilled orders against the capacity utilization-based shift variable and shows that a decline in the shift variable is associated with a rise in unfilled orders. This pattern is consistent with the presence of material constraints, as documented by Balleer and Noeller (2024) using German firm-level data.[9]

Our identified capacity utilization-based shift variable aligns with the cyclical capacity shocks studied by Comin et al. (2023). Under the Federal Reserve's definition of capacity as "sustainable maximum output," temporary supply disruptions primarily manifest as reductions in the output index rather than the capacity index.

Relatedly, Boehm and Pandalai-Nayar (2022) focus on demand shocks to identify the

[9]We do not construct an instrument based on unfilled orders as this variable is only available for a subset of manufacturing industries, which would substantially reduce cross-industry variation in j.

convexity of the supply curve in the manufacturing sector, particularly when firms operate at or near full capacity. Unlike their approach, which emphasizes demand-side variation, our analysis seeks to capture upstream supply shocks through observed changes in capacity utilization, which we regard as a relevant instrument in our context.

3.6 Interpretation of the pricing response

Our findings suggest that retail prices tend to rise in response to exogenous supply disruptions that reduce retailers' inventory holdings, even after accounting for a broad set of controls, including measures of input costs. In the context of the NKPC literature, this evidence aligns with a strand of research emphasizing the role of time-varying retail price markups in shaping inflation dynamics. The next section builds on this perspective by further exploring its implications.

That said, we acknowledge that alternative interpretations of our results are possible and warrant further investigation. First, given our reliance on industry-level data, we are unable to observe the composition of retail goods. Retailers may respond to supply disruptions by shifting toward higher-margin products, which would mechanically raise measured price margins without requiring active price increases. Second, we cannot rule out unobserved cost pressures. In particular, absent data on retailers' expectations of future marginal costs, it remains possible that firms raise prices to maintain rather than expand markups. Third, we remain agnostic on manufacturer markups and do not study their interaction with retailer markups—a topic examined in detail by Alvarez-Blaser et al. (2025) using data from a large global manufacturer. These alternative mechanisms highlight the need for richer data to fully disentangle pricing responses, which we leave for future work.

4 The NKPC with inventories

Our empirical investigation reveals a significantly positive response in the retail price margin to supply disruptions that adversely affect the stocking behavior of the retail industry. Building on this relationship, we examine whether the systematic link between the dynamics of the retail inventory-sales ratio and the retail price markup can help improve the empirical performance of the NKPC.

To address this question, we extend the stylized model introduced in Section 2. Specifically, we incorporate inventory management into the retail sector and introduce two standard sources of state-dependent price markups: the demand specification of Kimball (1995) and the deep habits framework of Ravn et al. (2006). These mechanisms generate time-varying price margins that align with our empirical findings and are widely utilized in the literature on inflation and business cycles.

Subsequently, we derive two representations of the linearized NKPC with inventories. We demonstrate that incorporating the retail inventory-sales ratio as an observable variable in the NKPC effectively captures time-varying price markups, which are otherwise difficult to measure directly.

4.1 Demand function

We first derive the retailers' demand function. To introduce time-varying price markups even without nominal rigidities, we specify the following aggregator where the aggregate habit-adjusted consumption, C_t, is implicitly defined as

$$\int_0^1 v_{j,t} \Upsilon \left(\frac{s_{j,t} - \theta s_{j,t-1}}{v_{j,t} C_t} \right) dj = 1.$$

The variables $s_{j,t}$ and $v_{j,t}$ denote the real sales and household preference of variety $j \in [0, 1]$ in period t, respectively. The parameter $\theta \in [0, 1]$ measures the degree of habit formation in consumption of each variety. This specification encompasses both the state-dependent demand elasticity *a la* Kimball (1995) and deep-habit formation in customer markets analyzed in Ravn et al. (2006). Following Klenow and Willis (2016), we assume the aggregator $\Upsilon(x)$ such that

$$\Upsilon'(x) = \left(\frac{\eta - 1}{\eta} \right) \exp \left(\frac{1 - x^{\frac{\psi}{\eta}}}{\psi} \right),$$

This function is consistent with CES when $\psi > 0$ approaches zero and $\eta > 1$ is the price elasticity of demand under CES. More generally, the price elasticity of demand is expressed as

$$-\left(\frac{ds_{j,t}}{dp_{j,t}}\right)\left(\frac{p_{j,t}}{s_{j,t}}\right)=\frac{\Upsilon'(x_{j,t})}{x_{j,t}\Upsilon''(x_{j,t})}\frac{s_{j,t}-\theta s_{j,t-1}}{s_{j,t}}=\eta x_{j,t}^{-\frac{\psi}{\eta}}\frac{s_{j,t}-\theta s_{j,t-1}}{s_{j,t}},$$

where $x_{j,t}\equiv(s_{j,t}-\theta s_{j,t-1})/(v_{j,t}C_t)$. As discussed above, the price elasticity of demand is η in the special case of CES ($\theta=\psi=0$). Otherwise when $\theta>0$ or $\psi>0$, the price elasticity of demand varies due to its state and history dependence, allowing more flexibility for the model to be consistent with our empirical findings of a negative inventory stock elasticity of the price margin.

As shown in the Appendix, the variety j demand function is derived as follows:

$$s_{j,t}=v_{j,t}C_t\Upsilon'^{-1}\left(\frac{p_{j,t}}{P_t}D_t\right)+\theta s_{j,t-1}, \tag{9}$$

where the demand index D_t is defined as

$$D_t=\int_0^1\Upsilon'\left(\frac{s_{j,t}-\theta s_{j,t-1}}{v_{j,t}C_t}\right)\frac{s_{j,t}-\theta s_{j,t-1}}{C_t}dj,$$

and the price index P_t is implicitly defined in

$$1=\int_0^1 v_{j,t}\Upsilon\left(\Upsilon'^{-1}\left(\frac{p_{j,t}}{P_t}D_t\right)\right)dj.$$

4.2 The retail firm problem

The monopolistically competitive retail firm j in period t purchases $y_{j,t}$ quantity of manufacturing goods at a unit price Q_t. It differentiates the good which is then stocked and sold to households at a price $p_{j,t}$. The stock of retail goods, $a_{j,t}$, is the sum of the undepreciated inventories from the previous period and the goods purchased in the current period:

$$a_{j,t}=(1-\delta)inv_{j,t-1}+y_{j,t}, \tag{10}$$

where $inv_{j,t-1}$ is the end-of-period inventories in period $t-1$ and δ is the inventory depreciation rate. In turn, the end-of-period inventories evolve as follows:

$$inv_{j,t} = a_{j,t} - s_{j,t}. \tag{11}$$

Dividing each side by $s_{j,t}$, we obtain a relationship between the inventory-sales ratio and the stock-sales ratio. Since they differ only by a constant, the two ratios move together. The inventory-sales ratio is defined as:

$$is_{j,t} = \frac{inv_{j,t}}{s_{j,t}}.$$

Demand for the retail good is given in (9). Following Bils and Kahn (2000) and Jung and Yun (2005), we assume that demand is also elastic to the stock of goods for sale:

$$v_{j,t} = \left(\frac{a_{j,t}}{A_t}\right)^{\zeta}, \tag{12}$$

where ζ is the sales elasticity to the stock of goods.[10] The aggregate stock is defined as

$$A_t = \left(\int_0^1 a_{j,t}^{\zeta} dj\right)^{\frac{1}{\zeta}}.$$

Nominal price rigidity is introduced *a la* Rotemberg (1982). In detail, the retail firm faces a quadratic price adjustment cost in the following form:

$$\frac{\nu_p}{2}\left(\frac{p_{j,t}}{p_{j,t-1}} - 1\right)^2 P_t S_t, \tag{13}$$

where ν_p represents the degree of nominal price rigidity and $S_t = \int_0^1 s_{j,t} dj$ is aggregate sales.

[10] We do not employ a stockout avoidance model, as the presence of deep habits introduces rich dynamics that make it difficult to track the relevant idiosyncratic state variables. As noted by Crouzet and Oh (2016) in the context of news shocks and by Kryvtsov and Midrigan (2013) for monetary policy shocks, the stock-elastic demand specification and the stockout avoidance model exhibit similar equilibrium implications for inventory dynamics, particularly with respect to the endogeneity of inventory-sales ratios.

The retail firm maximizes the expected discounted sum of profits:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t} \Phi_{j,t},$$

where the period-t profit of the retailer is

$$\Phi_{j,t} = p_{j,t} s_{j,t} - Q_t y_{j,t}.$$

The retailer is subject to the above conditions (9)-(13). The full optimality conditions are presented in the Appendix.

4.3 Deriving the NKPC with inventories

In standard New Keynesian models without inventories, the NKPC is obtained by combining the firm's pricing decision with its sales condition, under the assumption that the firm satisfies all demand at its chosen price. Implicit in this setup is that the retail firm's stocking decision is equivalent to its production and sales decision.

With inventories, this equivalence breaks down: retailers can satisfy demand not only by purchasing new goods but also by drawing down existing stocks. This distinction introduces an additional margin of adjustment and implies that there are multiple routes to deriving the NKPC. Below, we present the key equilibrium conditions that give rise to alternative representations of the NKPC.

4.3.1 Equilibrium pricing condition

The log-linearized optimal pricing condition in symmetric equilibrium is

$$\hat{\pi}_t = \beta \mathbb{E}_t \hat{\pi}_{t+1} - \frac{1}{\nu_p} (\hat{\kappa}_t + \hat{c}_t - \hat{s}_t), \tag{14}$$

where hatted values denote log-deviations from the noninflationary steady state, and κ_t is the real marginal benefit of an additional unit of sales in period t—the Lagrange multiplier on the demand constraint (9), capturing the inframarginal revenue effect. Current inflation therefore depends on expected future inflation, the real marginal benefit of sales, and the gap between habit-adjusted consumption and sales. This condition also applies in the model without inventories. The key difference between models with and without inventories lies in how demand is met, as summarized by κ_t. In the model with inventories, κ_t is not directly linked to contemporaneous real marginal cost because retailers can satisfy demand by drawing down existing inventories rather than immediately purchasing additional goods to restock.

4.3.2 Sales-based NKPC

The log-linearized optimal sales condition is

$$\hat{\kappa}_t = \theta\beta\mathbb{E}_t(\hat{r}_{t,t+1} + \hat{\kappa}_{t+1}) - \left[\eta(1-\theta)\left(1+\psi\ln\left(\frac{\eta-1}{\eta}\right)\right)^{-1} - 1 + \theta\beta\right]\mathbb{E}_t(\hat{r}_{t,t+1} + \widehat{mc}_{t+1}), \tag{15}$$

where $r_{t,t+1}$ is the real stochastic discount factor between period t and $t+1$ and mc_t the real marginal cost of producing a retail good in period t, equivalently the Lagrange multiplier on the law of motion for the inventory stock (10).

To interpret this condition, it is helpful to begin with the benchmark New Keynesian model without inventories and with CES preferences across varieties ($\theta = \psi = 0$). The sales condition then reduces to

$$\hat{\kappa}_t = -(\eta-1)\widehat{mc}_t.$$

Because the markup without inventories is the inverse of real marginal cost, this relation shows that the real marginal benefit of sales is proportional to the markup. Substituting this expression into (14) yields the familiar Rotemberg-type NKPC:[11]

$$\hat{\pi}_t = \beta\mathbb{E}_t\hat{\pi}_{t+1} + \left(\frac{\eta-1}{\nu_p}\right)\widehat{mc}_t.$$

In this benchmark, the sales and stocking conditions coincide, since all sales must be met by contemporaneous purchases of goods. This equivalence implies a one-for-one mapping

[11] Without habits ($\theta = 0$), consumption equals sales so that $\hat{c}_t = \hat{s}_t$.

between marginal cost and the marginal benefit of sales, which is why the standard NKPC can be written directly in terms of real marginal cost.

With inventories, however, this one-for-one mapping breaks down. Additional sales need not be met by contemporaneous purchases. Instead, the retailer recognizes that sales can be satisfied by drawing down inventories, so the optimal sales decision depends on the expected discounted future marginal cost rather than on the current marginal cost. When $\theta > 0$, habit formation adds an additional intertemporal channel: the expected discounted marginal benefit of future sales also matters. Combining (14) and (15) yields the following sales-based NKPC.

Proposition 1 (Sales-based NKPC)**.** *The sales-based NKPC is derived by combining* (14) *and* (15)*:*

$$\hat{\pi}_t = \beta \mathbb{E}_t \hat{\pi}_{t+1} + B_1 \mathbb{E}_t (\hat{r}_{t,t+1} + \widehat{mc}_{t+1}) - B_2 \mathbb{E}_t (\hat{r}_{t,t+1} + \hat{\kappa}_{t+1}) + B_3 (\hat{s}_t - \hat{c}_t),$$

where

$$B_1 = \frac{1}{\nu_p} \left[\eta(1-\theta) \left(1 + \psi \ln \left(\frac{\eta - 1}{\eta} \right) \right)^{-1} - 1 + \theta\beta \right], \quad B_2 = \frac{\theta\beta}{\nu_p}, \quad B_3 = \frac{1}{\nu_p}.$$

In the CES case ($\theta = \psi = 0$), the sales-based NKPC simplifies to

$$\hat{\pi}_t = \beta \mathbb{E}_t \hat{\pi}_{t+1} + \left(\frac{\eta - 1}{\nu_p} \right) \mathbb{E}_t (\hat{r}_{t,t+1} + \widehat{mc}_{t+1}).$$

There are two main takeaways. First, without habits, expected future inflation and expected discounted real marginal cost are sufficient statistics for current inflation. Second, with habits, the sales-based NKPC is generally difficult to estimate empirically because it requires separate measures of the real marginal benefit of sales and the marginal cost.

4.3.3 Stock-based NKPC

Inventories also give rise to the equilibrium stocking condition, which characterizes how retailers choose inventory holdings. The log-linearized condition is

$$\hat{a}_t = \hat{c}_t + \frac{1}{1-\beta(1-\delta)}[\beta(1-\delta)\mathbb{E}_t(\hat{r}_{t,t+1} + \widehat{mc}_{t+1}) - \widehat{mc}_t] + \hat{\kappa}_t. \tag{16}$$

This condition highlights three key determinants of the retailer's stocking decision. First, *aggregate demand* ($\hat{c}_t$) matters, as retailers target a desired inventory-sales ratio; higher expected sales translate into higher desired stocks. Second, the *intertemporal substitution channel in stocking* captures the difference between the expected discounted future marginal cost and the current marginal cost: when costs are expected to rise, firms have an incentive to buy more today and carry inventories forward. This channel parallels the mechanism emphasized by Crouzet and Oh (2016). Third, the term $\hat{\kappa}_t$ reflects the *real marginal benefit of sales*: holding more stock increases sales capacity and boosts expected profits, reinforcing the incentive to accumulate inventories.

Substituting out $\hat{\kappa}_t$ and denoting $\overline{IS}$ as the steady-state inventory-sales ratio, we obtain the following stock-based NKPC.

Proposition 2 (Stock-based NKPC)**.** *The stock-based NKPC is derived by combining* (14) *and* (16)*:*

$$\hat{\pi}_t = \beta\mathbb{E}_t\hat{\pi}_{t+1} + \tilde{B}_1[\beta(1-\delta)\mathbb{E}_t(\hat{r}_{t,t+1} + \widehat{mc}_{t+1}) - \widehat{mc}_t] - \tilde{B}_2\widehat{is}_t,$$

where

$$\tilde{B}_1 = [\nu_p(1-\beta(1-\delta))]^{-1}, \quad \tilde{B}_2 = \overline{IS}(\nu_p(\overline{IS}+1))^{-1}.$$

Two insights stand out. First, inflation is driven by three observable statistics: expected future inflation, the expected change in discounted real marginal cost, and the inventory-sales ratio. Second, this representation is agnostic to the sources of endogenous markup variation arising from the Kimball aggregator or deep habits, since these demand effects are absorbed by the inventory-sales ratio. The dynamics of the ratio thus serve as a sufficient statistic for markup behavior in a wide class of models, including CES, Kimball demand, and deep habits.

4.4 Discussion

We find that the stock-based NKPC offers greater flexibility by remaining agnostic about the sources of time-varying markups. Its key observable is the inventory-sales ratio, which—after purging the intertemporal substitution channel—primarily captures the inflationary role of the marginal benefit of sales, i.e., markups. This provides an empirically tractable proxy for time-varying markups in inflation dynamics, which we analyze in the next section.

It is also worth noting that, while our industry-level IV results exploit exogenous variation from short-lived supply disruptions, the stock-based NKPC does not take a stand on the origin of shocks. Its relative improvement in fit should therefore not be interpreted as evidence of the importance of supply disruptions *per se*, since any inflationary disturbance can propagate through inventories. Put differently, while our IV strategy isolates shifts in the stocking curve, the fluctuations in the inventory-sales ratio that enter the stock-based NKPC reflect both shifts of the curve and endogenous movements along it.

5 Empirical Phillips curve with inventories

In this section, we estimate the stock-based NKPC on macroeconomic data and show that it outperforms both the canonical specification and the sales-based NKPC under CES demand. The improvement comes from including the inventory-sales ratio as an observable, which captures the time-varying markup channel missing from standard NKPCs. We further show that this specification accounts for two prominent episodes—the 2009–2011 missing disinflation and the COVID-era surge—underscoring the role of inventories as an indicator of inflationary pressures.

5.1 Empirical specification and data

We estimate three reduced-form (semi-structural) Phillips curve specifications with theory-motivated exclusion and equality restrictions:

$$\hat{\pi}_t = \alpha_0 + \alpha_1 \hat{\pi}_{t-1} + \alpha_2 \mathbb{E}_t \hat{\pi}_{t+1} + \alpha_3 \widehat{mc}_t + \alpha_4 (\mathbb{E}_t \hat{r}_{t,t+1} + \mathbb{E}_t \widehat{mc}_{t+1}) + \alpha_5 \widehat{is}_t + \varepsilon_t, \tag{17}$$

where ε_t denotes the regression error. The first sets $\alpha_4 = \alpha_5 = 0$, yielding the canonical NKPC without inventories, as in Galí and Gertler (1999), with both backward- and forward-looking inflation expectations. The second sets $\alpha_3 = \alpha_5 = 0$, corresponding to the sales-based NKPC under CES demand (Proposition 1). The third imposes the equality restriction $\alpha_3 = -\alpha_4$, delivering the stock-based NKPC (Proposition 2) with expected marginal cost growth expressed under zero inventory depreciation and no average time discounting.[12]

To estimate these regressions, we compile macroeconomic variables at quarterly frequency. Since retail inventory management is primarily relevant within the goods sector, our analysis focuses on accounting for goods inflation, though we also report results using headline inflation for comparison. Accordingly, our baseline regression defines $\hat{\pi}_t$ as the annualized quarterly inflation of the goods component of Personal Consumption Expenditures (PCE). For expected inflation $\mathbb{E}_t \hat{\pi}_{t+1}$, we use both the mean professional inflation forecast from the Survey of Professional Forecasters (SPF) and the mean household inflation forecast from the Michigan Survey, each reflecting year-ahead expectations. To our knowledge, no survey provides separate forecasts specifically for goods inflation. By estimating an unrestricted coefficient on inflation expectations, we allow for proportionality between expectations of headline and goods inflation.

To proxy for the real marginal cost, $\widehat{mc}_t$, we use the inverse of the unemployment gap, a commonly used measure of economic slack (e.g., Stock and Watson, 2020). Specifically, we define the unemployment gap as the difference between the quarterly unemployment rate and the quarterly estimate of the Non-Accelerating Inflation Rate of Unemployment (NAIRU) from the Congressional Budget Office (CBO). Because our Phillips curve specification includes expected future real marginal cost, $\mathbb{E}_t \widehat{mc}_{t+1}$, using the unemployment gap is

[12] Although results are robust to relaxing the restriction, estimating α_3 and α_4 separately induces multicollinearity due to the high correlation between current and expected marginal cost.

particularly useful, as we can construct a comparable expectation-based proxy. We define the expected future unemployment gap as the difference between the SPF's year-ahead unemployment forecast and the year-ahead NAIRU estimate from the CBO.

Alternative proxies for the real marginal cost used in the literature include the output gap, the labor share, the vacancy-to-unemployment ratio, and unit labor cost. Because the NKPC model with inventories requires a measure of expected future real marginal cost, however, constructing such a measure using these alternatives is more challenging.[13]

We define the expected real interest rate, $\mathbb{E}_t \hat{r}_{t,t+1}$, as the effective Federal Funds rate minus the SPF's year-ahead inflation forecast.

Finally, for the inventory-sales ratio, $\widehat{is}_t$, we aggregate inventory and sales data from the retail and wholesale sectors. We detrend this variable using the Hamilton (2018) filter.

The sample spans 1983q3–2025q1. The inventory-sales ratio is constructed from 1980q4 onward—when wholesale inventories become available—and this earlier start is used to implement the Hamilton filter, which regresses the ratio on its 8th–11th lags.

5.2 NKPC regression results

We now present regression estimates for the three Phillips curve specifications.

5.2.1 Evidence for the stock-based NKPC

Our derivation of multiple NKPC representations is useful because, under CES demand, the sales-based and stock-based specifications should be empirically equivalent. If their empirical fit differs in favor of the stock-based specification, this provides evidence against CES and, through the lens of our model, implies that aggregate inflation dynamics require channels of time-varying markups beyond those captured by nominal rigidity.

Table 3 reports OLS estimates of the three specifications in equation (17), using goods and headline PCE inflation as dependent variables and SPF inflation expectations. For goods inflation, the stock-based NKPC in column (3) attains a noticeably higher adjusted R-squared than both the canonical specification (col. 1) and the sales-based NKPC under

[13]Nevertheless, in the Appendix we show that our main results are robust to the choice of the marginal cost proxy in a canonical NKPC specification augmented with the inventory-sales ratio, suggesting that our findings are unlikely to be driven by the specific proxy used.

Table 3: NKPC Estimates for Goods and Headline Inflation (SPF Expectations)

	Goods PCE Inflation			Headline PCE Inflation		
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged inflation	0.342**	0.343***	0.047	0.455***	0.463***	0.197
	(0.131)	(0.130)	(0.100)	(0.135)	(0.140)	(0.120)
Exp. inflation (SPF)	0.369	0.373	1.173**	0.321**	0.263**	0.665***
	(0.284)	(0.250)	(0.459)	(0.160)	(0.128)	(0.225)
Marginal cost	0.030			0.074		
	(0.145)			(0.063)		
Exp. marginal cost		0.001			0.038	
		(0.092)			(0.047)	
Exp. marginal cost growth			0.048			0.089
			(0.166)			(0.094)
IS ratio			-0.430***			-0.189***
			(0.092)			(0.048)
Constant	-0.282	-0.319	-2.299**	0.461	0.548*	-0.028
	(0.868)	(0.761)	(1.158)	(0.313)	(0.299)	(0.530)
Observations	167	167	167	167	167	167
Adjusted R-squared	0.130	0.130	0.375	0.315	0.313	0.500

Notes: Variable definitions are provided in the main text. Expected inflation is from the SPF; results using the Michigan Survey are reported in the Appendix. Newey–West standard errors are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

CES demand (col. 2). The same pattern holds for headline inflation: column (6) dominates columns (4) and (5). The better fit of the stock-based NKPC relative to the CES-demand specification indicates that the data favor our non-CES specification with time-varying markups. Taken together with the industry-level evidence, these results provide plausible evidence that time-varying markups matter for inflation dynamics.[14]

[14] In the Appendix, we show that other metrics such as the Akaike information criterion or the one-quarter-ahead root mean squared errors, which also generally favor the stock-based NKPC.

5.2.2 Why the stock-based NKPC fits better: The role of inventories

Why does the stock-based NKPC fit better? Inspecting columns (3) and (6), the inventory-sales ratio enters with a negative and statistically significant coefficient, as predicted by equation (16), while variables related to marginal cost dynamics—including both current and expected marginal cost—are not significant. The magnitudes are economically meaningful: a one-standard-deviation decline in the inventory-sales ratio is associated with roughly a 2 percentage-point and 0.9 percentage-point increase in goods and headline inflation, respectively. By comparison, a one-standard-deviation rise in SPF expected inflation is associated with about 1.1 percentage points and 0.6 percentage points, respectively. Thus, the inventory-sales ratio plays an important role in accounting for inflation dynamics, likely through goods prices.

These findings are robust across a wide range of specifications and data choices. In the Appendix, we show that they are robust to using the Michigan Survey for inflation expectations. In addition, re-estimating the model with alternative marginal cost proxies commonly used in the literature confirms that the inventory-sales ratio remains a strong and significant predictor of inflation.[15] We further estimate the NKPC using core goods inflation—adjusting the inventory-sales ratio accordingly—and again find results consistent with our main conclusion. Finally, testing a nonlinear specification of the inventory term shows that the linear mechanism continues to dominate.

5.2.3 Orthogonal contribution of inventories

To isolate the contribution of the inventory–sales ratio in the stock-based NKPC and compare it with other regressors, we report the semipartial R-squared. Following the Frisch-Waugh-Lovell logic, we orthogonalize each regressor with respect to the other controls and then computing its explanatory power. This statistic captures the regressor's unique (orthogonal) contribution and, in general, does not sum to total R-squared across regressors. Recall that, in our framework, the component of the inventory-sales ratio orthogonal to expected marginal cost growth primarily reflects movements in time-varying markups; ac-

[15] As discussed earlier, we estimated the canonical NKPC augmented with the inventory-sales ratio, rather than the stock-based NKPC, because expected marginal cost proxies are not available for this robustness check.

Table 4: Semipartial R-squared (Unique Contribution of Regressors)

	Goods PCE Inflation	Headline PCE Inflation
Panel A: SPF Expectations		
Lagged inflation	0.16	2.39
Exp. inflation	4.24	5.03
Exp. marginal cost growth	0.04	0.56
IS ratio	24.43	18.86
Total R-squared	39.03	51.18
Panel B: Michigan Expectations		
Lagged inflation	0.02	0.08
Exp. inflation	9.08	12.23
Exp. marginal cost growth	1.54	5.04
IS ratio	15.07	10.62
Total R-squared	43.87	58.38

Notes: Semipartial R-squared values report each regressor's marginal contribution conditional on all others. All values are percentages.

cordingly, its semipartial R-squared provides a conservative measure of the markup channel.

Table 4 reports results for both goods and headline inflation using expectations from either the SPF or the Michigan Survey. For SPF expectations (Panel A), the inventory-sales ratio accounts for a substantial 24.4 percent, far exceeding the marginal cost and inflation expectations channels in terms of orthogonal contributions. This indicates that variation in the inventory-sales ratio orthogonal to marginal cost and inflation expectations is quantitatively important for goods inflation. A similar, though smaller, role appears for headline inflation, where the inventory-sales ratio's semipartial R-squared is about 18.9 percent.

With Michigan expectations (Panel B), expected inflation absorbs a larger share of variation in goods inflation (about 9.1 percent). Even so, the inventory-sales ratio remains the single largest semipartial R-squared component (roughly 15 percent). For headline inflation, expected inflation contributes more (about 12.2 percent) than the inventory-sales ratio (about 10.6 percent), but the latter remains economically meaningful. In both cases, the inventory-sales ratio adds distinct, orthogonal information not contained in Michigan expectations and therefore complements them in accounting for inflation dynamics.

5.3 The stock-based NKPC and recent inflation episodes

Having established the superior fit of the stock-based NKPC in the full sample, we next examine whether the framework can also account for two specific inflation episodes that have attracted considerable attention in the literature.

5.3.1 The 2009–2011 missing disinflation puzzle

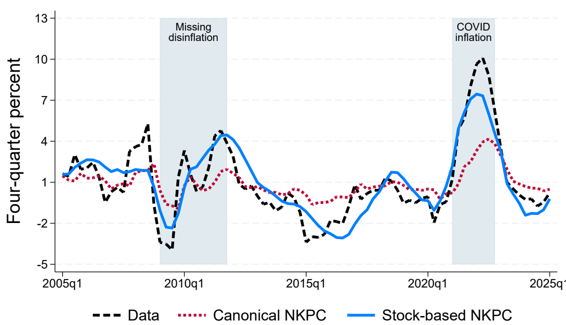
The 2009–2011 missing disinflation puzzle has been widely discussed in the literature, with a prominent resolution proposed by Coibion and Gorodnichenko (2015). Using the SPF, they show that a version of the canonical NKPC substantially underpredicts inflation over this period. However, when substituting inflation expectations from the Michigan Survey—where household expectations rose more sharply—the puzzle largely disappears. This implies that the puzzle is conditional on the choice of the inflation expectation measure, particularly the SPF.

We offer an alternative explanation using the stock-based NKPC while still conditioning on SPF expectations. Panel C of Figure 3 plots actual headline PCE inflation alongside inflation predicted by both the canonical and stock-based NKPCs. The canonical specification predicts four-quarter inflation to remain below 2 percent between 2009 and 2011 (the first shaded region), while observed inflation reached 3 percent. In contrast, the stock-based NKPC successfully tracks the actual inflation path. This improvement coincides with a period of below-trend inventory-sales ratios, consistent with widespread inventory liquidation by financially constrained firms following the 2008 credit shock, as analyzed by Kim (2021).

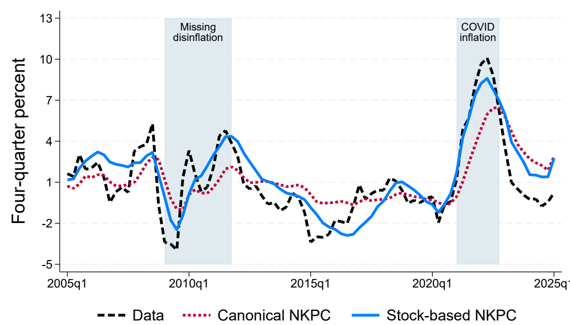
For comparison, Panel D uses a specification similar to Coibion and Gorodnichenko (2015) with Michigan inflation expectations. In this case, the canonical NKPC also aligns more closely with observed inflation, and the stock-based NKPC remains consistent with the data.

FIGURE 3: Model Fit

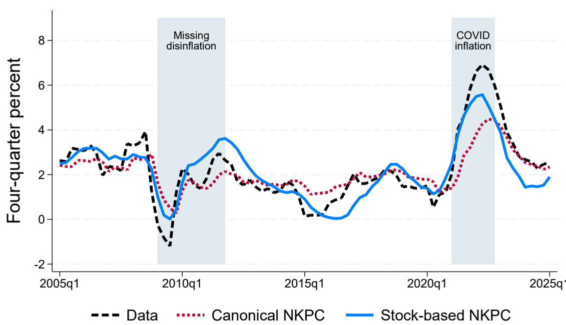
(A) Goods PCE Inflation – SPF



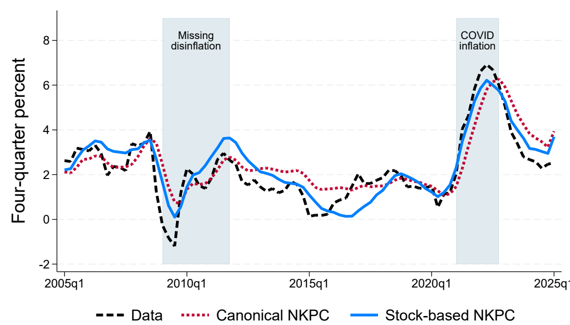
(B) Goods PCE Inflation – Michigan



(C) Headline PCE Inflation – SPF



(D) Headline PCE Inflation – Michigan



Notes: Panel A shows the model fit to goods PCE inflation using year-ahead SPF inflation forecasts. Panel B presents the model fit to goods PCE inflation using year-ahead Michigan inflation forecasts. Panel C shows the model fit to headline PCE inflation with year-ahead SPF forecasts, while Panel D presents the fit using year-ahead Michigan forecasts. In all panels, the first shaded region corresponds to 2009q1–2011q4 and the second to 2021q1-2022q4.

5.3.2 The COVID-era inflation surge

The stock-based NKPC also captures the surge in inflation—particularly for goods—during the COVID period. As shown in Panels A and B of Figure 3, goods inflation rose to 10 percent between 2021 and 2022 (the second shaded region), a surge that the stock-based NKPC better tracks in both panels. In contrast, the canonical NKPC explains only a smaller portion of the rise, predicting a peak inflation of roughly 4 percent when using SPF expectations (Panel A) and 6 percent with Michigan expectations (Panel B). Moreover, the stock-based NKPC better captures the sharp reversal in goods inflation following the peak, underscoring the complementary role of the inventory-sales ratio in accounting for goods inflation dynamics, especially during periods of swift adjustment.

Turning to headline inflation, the tight inventory-sales ratio, which played a central role in the surge in goods inflation, also contributed significantly to the rise in headline inflation. The stock-based NKPC not only better matches the magnitude of the headline surge than the canonical specification, but also more accurately predicts its earlier timing—showing a peak that arrives sooner and aligns more closely with the data. This improvement is pronounced when using SPF expectations (Panel C), and while the magnitude remains similar with Michigan expectations (Panel D), the earlier predicted peak remains consistent with the observed timing.[16]

6 Conclusion

This paper investigates whether the retail price margin channel—whereby inventory scarcity amplifies retail price margins—can help explain observed inflation dynamics. By modeling the retailer's joint decision over pricing and inventory management, and constructing industry-level instruments from supply chain disruptions that plausibly affect only the retailer's stocking behavior, we identify the elasticity of price margins with respect to inventory stocks. We estimate this elasticity to be negative, implying that tighter retail inventories are systematically associated with higher price margins. This evidence supports the view that retail prices are shaped not only by cost-push factors but also by the strategic pricing behavior of firms facing inventory constraints.

Integrating this mechanism into a NKPC framework, we show that the inventory-sales ratio serves as a powerful and observable proxy for retail markups. The resulting stock-based NKPC delivers a substantially improved empirical fit, successfully capturing key inflationary episodes such as the 2009–2011 missing disinflation and the COVID-era surge that originated from the goods sector. These findings suggest that incorporating retail inventory dynamics enhances our understanding of inflation—particularly during periods when supply chains are constrained—by capturing a critical source of time-varying markups

[16]In the Appendix, COVID-era pseudo-out-of-sample inflation forecasts show a similar pattern, though all models exhibit a delayed pickup in inflation relative to the data.

often overlooked in standard NKPC models.

Looking ahead, several avenues for further research remain. One is to examine how inventory dynamics interact with nonlinear NKPC specifications, for example by allowing the slope of the Phillips curve to vary across regimes of inventory tightness or demand pressure. Another is to investigate whether the inventory-based mechanism can account for the time variation in the slope of the NKPC documented in the empirical literature. More broadly, extending the framework to incorporate sectoral heterogeneity or to model the interaction between retail inventories and upstream supply chain frictions could yield new insights into how microeconomic bottlenecks shape aggregate inflation dynamics.

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Online Appendix to *Retail inventories and inflation dynamics: The price margin channel*

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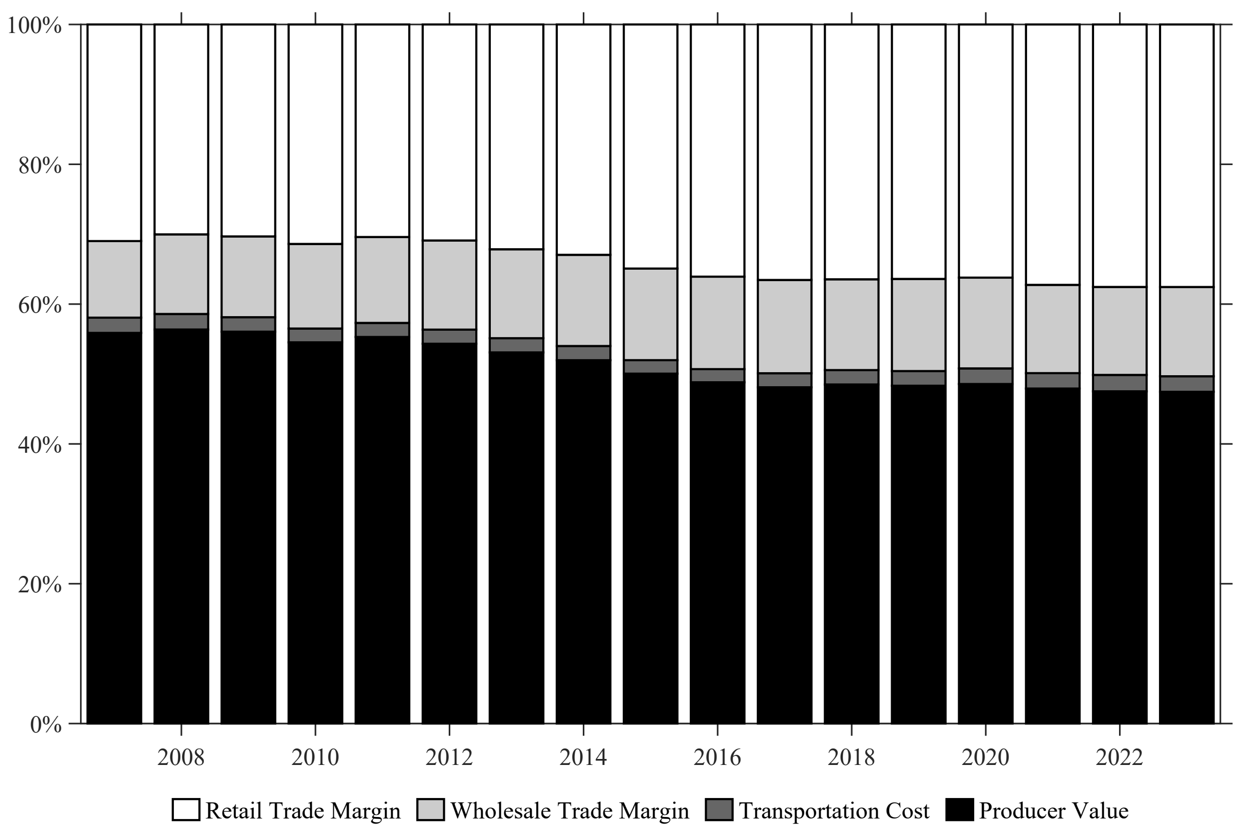
A Appendix to Section 1

To calculate the share of retail and wholesale trade margins in the purchasers' value of PCE goods, we use the PCE bridge summary table published by the BEA. Figure A.1 shows the annual composition between 2007 and 2023. Producers' value accounts for roughly 50 percent of purchasers' value, a share that has gradually declined over time. Retail margins represent between 30 and 40 percent, with their share rising in recent years. Wholesale margins remain around 10 percent, while transportation costs account for only a small share.

FIGURE A.1: Breakdown of Purchasers' Value for PCE Goods



Notes: Data come from the PCE bridge table published by the BEA. Bars show producers' value, transportation cost, wholesale trade margin, and retail trade margin as shares of purchasers' value for PCE goods.

B Appendix to Section 3

B.1 Industry regressions: Controlling for other input costs

For regression (3), we can also control for non-capital and non-labor costs from the BLS satellite series of *net inputs to industry price indexes*, which are available only from 2019 onward (see `https://www.bls.gov/ppi/input-indexes`). This shortens the sample and makes the estimates noisier. Nonetheless, as reported in Table B.1, the results remain broadly consistent with our baseline, indicating that our main conclusions are robust to the inclusion of these additional cost controls.

Table B.1: Industry Regression Results (Controlling for Other Input Costs)

	OLS	IV		
	PPI	GSCPI	ACR	CU
Panel A: Three-Month Difference ($k = 3$)				
IS ratio	-0.230	-0.491***	-1.358*	-0.595***
	(0.177)	(0.177)	(0.710)	(0.149)
First-stage F-stat		18.18	4.65	10.47
AR Wald F p-value		0.015	0.005	0.008
Observations	273	288	248	273
Sample	2019m6–2025m6	2019m6–2025m6	2019m6–2024m6	2019m6–2025m6
Panel B: Six-Month Difference ($k = 6$)				
IS ratio	-0.549***	-1.126*	-1.455***	-0.919*
	(0.185)	(0.592)	(0.429)	(0.519)
First-stage F-stat		3.41	6.16	4.82
AR Wald F p-value		0.010	0.047	0.068
Observations	243	273	233	273
Sample	2019m6–2025m6	2019m6–2025m6	2019m6–2024m6	2019m6–2025m6

Notes: Driscoll–Kraay standard errors are reported in parentheses. Instruments for the IV columns are: Global Supply Chain Pressure Index (GSCPI), Average Congestion Rate (ACR), and upstream capacity utilization shocks (CU). * p<0.10, ** p<0.05, *** p<0.01.

B.2 Industry regressions: First stage

The first-stage regression results for our three instruments are reported in Table B.2. All three instruments are negatively associated with the retail inventory-sales ratio—both for three- and six-month growth rates—consistent with the intuition that greater supply disruptions constrain retailers' ability to restock inventories.

Table B.2: Industry Regression Results (First Stage)

	Z^{GSCPI}	Z^{ACR}	Z^{CU}
Panel A: Three-Month Difference ($k = 3$)			
Coefficient	-0.876***	-9.889***	1.502***
	(0.294)	(3.776)	(0.331)
Observations	1824	792	1808
Adjusted R-squared	0.804	0.769	0.738
Sample	2005m1–2025m6	2017m1–2025m6	2005m1–2024m6
Panel B: Six-Month Difference ($k = 6$)			
Coefficient	-1.331***	-17.73***	1.690***
	(0.330)	(4.131)	(0.354)
Observations	1784	792	1832
Adjusted R-squared	0.604	0.606	0.606
Sample	2005m1–2025m6	2017m1–2025m6	2005m1–2025m6

Notes: Driscoll–Kraay standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C Appendix to Section 4

In this section, we provide details on how we derived the non-CES demand function and several necessary equations based on that. We also provide the retailers' full optimality conditions.

C.1 Deriving the demand function

Households minimize the cost in choosing each variety to satisfy the habit-adjusted consumption variety:

$$c_{j,t} \equiv s_{j,t} - \theta s_{j,t-1},$$

taking as given the variety price as well as habits formed in the previous period:

$$\min_{c_{j,t}} \int_0^1 p_{j,t} c_{j,t} dj \quad \text{subject to} \quad \int_0^1 v_{j,t} \Upsilon\left(\frac{c_{j,t}}{v_{j,t} C_t}\right) dj = 1.$$

The first order condition for each variety can be written as

$$p_{j,t} = \frac{\lambda_t^p}{C_t} \Upsilon'\left(\frac{c_{j,t}}{v_{j,t} C_t}\right),$$

where λ_t^p is the lagrange multiplier of the implicit function. If we define P_t as a price index that satisfies

$$P_t C_t = \int_0^1 p_{j,t} c_{j,t} dj$$

in the optimum, we can invoke the Envelope theorem to get

$$P_t C_t = \lambda_t^p \int_0^1 \Upsilon'\left(\frac{c_{j,t}}{v_{j,t} C_t}\right) \frac{c_{j,t}}{C_t} dj.$$

Substituting out λ_t^p, we obtain

$$\Upsilon'\left(\frac{c_{j,t}}{v_{j,t}C_t}\right) = \frac{p_{j,t}}{P_t}\int_0^1 \Upsilon'\left(\frac{c_{j,t}}{v_{j,t}C_t}\right)\frac{c_{j,t}}{C_t}dj.$$

Therefore, the demand function could be expressed as

$$c_{j,t} = v_{j,t}C_t\Upsilon'^{-1}\left(\frac{p_{j,t}}{P_t}D_t\right),$$

where

$$D_t = \int_0^1 \Upsilon'\left(\frac{c_{j,t}}{v_{j,t}C_t}\right)\frac{c_{j,t}}{C_t}dj.$$

In terms of real sales, the demand function is

$$s_{j,t} = v_{j,t}C_t\Upsilon'^{-1}\left(\frac{p_{j,t}}{P_t}D_t\right) + \theta s_{j,t-1}. \tag{C.1}$$

Note that the value of P_t could only be implicitly derived by plugging the demand function back into the implicit function for the aggregator C_t:

$$1 = \int_0^1 v_{j,t}\Upsilon\left(\frac{c_{j,t}}{v_{j,t}C_t}\right)dj = \int_0^1 v_{j,t}\Upsilon\left(\Upsilon'^{-1}\left(\frac{p_{j,t}}{P_t}D_t\right)\right)dj.$$

C.2 Details of Klenow and Willis (2016)

Here, we derive several necessary equations of the Klenow and Willis (2016) specification of the Kimball (1995) aggregator. Note that the Kimball aggregator satisfies

$$\int_0^1 v_j\Upsilon(x_j)dj = 1,$$

where $x_j = c_j/(v_jC)$. In the case of CES,

$$\Upsilon_{CES}(x) = x^{\frac{\eta-1}{\eta}},$$

which implies that

$$C = \left(\int_0^1 v_j^{\frac{1}{\eta}} c_j^{\frac{\eta-1}{\eta}} dj\right)^{\frac{\eta}{\eta-1}}.$$

The following equations are useful benchmarks for the CES:

$$\begin{aligned}
\Upsilon'_{CES}(x) &= \frac{\eta-1}{\eta} x^{-\frac{1}{\eta}}, \\
\Upsilon'^{-1}_{CES}(x) &= \left(\frac{\eta-1}{\eta x}\right)^{\eta}, \\
(\Upsilon'^{-1}_{CES})'(x) &= -\frac{\eta}{x}\left(\frac{\eta-1}{\eta x}\right)^{\eta},
\end{aligned}$$

In the case of Klenow and Willis (2016), we have

$$\begin{aligned}
\Upsilon'_{KW}(x) &= \frac{\eta-1}{\eta} \exp\left(\frac{1-x^{\frac{\psi}{\eta}}}{\psi}\right), \\
\Upsilon'^{-1}_{KW}(x) &= \left(1+\psi \ln\left(\frac{\eta-1}{\eta x}\right)\right)^{\frac{\eta}{\psi}}, \\
(\Upsilon'^{-1}_{KW})'(x) &= -\frac{\eta}{x}\left(1+\psi \ln\left(\frac{\eta-1}{\eta x}\right)\right)^{-\frac{\psi-\eta}{\psi}}.
\end{aligned}$$

We can verify that the above expressions are consistent with CES when $\psi \to 0$.

Using the demand function (C.1), we have

$$p_j = \Upsilon'\left(\frac{s_j - \theta s_{j,-1}}{v_j C}\right) PD,$$

which implies that

$$\frac{dp_j}{ds_j} = \Upsilon''\left(\frac{s_j - \theta s_{j,-1}}{v_j C}\right) \frac{PD}{v_j C}.$$

Moreover, note that

$$-\frac{\Upsilon'(x)}{x\Upsilon''(x)} = \eta x^{-\frac{\psi}{\eta}}.$$

Therefore, the price elasticity of demand could then be written as

$$\eta(s_j) \equiv -\frac{d\ln s_j}{d\ln p_j} = -\frac{p_j}{s_j}\frac{ds_j}{dp_j} = \eta x_j^{-\frac{\psi}{\eta}}\left(\frac{s_j - \theta s_{j,-1}}{s_j}\right).$$

C.3 Full optimality conditions

C.3.1 Baseline with inventories

The lagrangian of the retailer is written as follows:

$$\mathcal{L} = \sum_{t=0}^{\infty}\mathbb{E}_0\Lambda_{0,t}\Bigg[p_{j,t}s_{j,t} - Q_t y_{j,t} + P_t mc_{j,t}\left\{y_{j,t} + (1-\delta)(a_{j,t-1} - s_{j,t-1}) - a_{j,t}\right\}$$
$$+P_t\kappa_{j,t}\left\{\left(\frac{a_{j,t}}{A_t}\right)^{\zeta}\Upsilon'^{-1}\left(\frac{p_{j,t}}{P_t}D_t\right)C_t + \theta s_{j,t-1} - s_{j,t}\right\} - \frac{\nu_p}{2}\left(\frac{p_{j,t}}{p_{j,t-1}} - 1\right)^2 P_t S_t\Bigg].$$

Taking the first order conditions, we get

$$\begin{aligned}
[p_{j,t}] : s_{j,t} &= -\kappa_{j,t}D_t C_t\left(\frac{a_{j,t}}{A_t}\right)^{\zeta}(\Upsilon'^{-1})'\left(\frac{p_{j,t}}{P_t}D_t\right) + \nu_p\frac{P_t S_t}{p_{j,t-1}}\left(\frac{p_{j,t}}{p_{j,t-1}} - 1\right) \\
&\quad - \nu_p\mathbb{E}_t\frac{\Lambda_{t,t+1}p_{j,t+1}P_{t+1}S_{t+1}}{p_{j,t}^2}\left(\frac{p_{j,t+1}}{p_{j,t}} - 1\right), \\
[a_{j,t}] : mc_{j,t} &= \zeta\kappa_{j,t}\left(\frac{a_{j,t}}{A_t}\right)^{\zeta-1}\Upsilon'^{-1}\left(\frac{p_{j,t}}{P_t}D_t\right)\frac{C_t}{A_t} + (1-\delta)\mathbb{E}_t\frac{\Lambda_{t,t+1}P_{t+1}}{P_t}mc_{j,t+1}, \\
[s_{j,t}] : \frac{p_{j,t}}{P_t} &= \kappa_{j,t} + \mathbb{E}_t\frac{\Lambda_{t,t+1}P_{t+1}}{P_t}((1-\delta)mc_{j,t+1} - \theta\kappa_{j,t+1}), \\
[y_{j,t}] : mc_{j,t} &= \frac{Q_t}{P_t}, \\
[mc_{j,t}] : a_{j,t} &= y_{j,t} + (1-\delta)(a_{j,t-1} - s_{j,t-1}), \\
[\kappa_{j,t}] : s_{j,t} &= \left(\frac{a_{j,t}}{A_t}\right)^{\zeta}\Upsilon'^{-1}\left(\frac{p_{j,t}}{P_t}D_t\right)C_t + \theta s_{j,t-1}.
\end{aligned}$$

The nominal stochastic discount factor between period t and $t+1$ could be written as the household's subjective discount factor β, the effective real stochastic discount factor $r_{t,t+1}$, and the price indices:

$$\Lambda_{t,t+1} = \beta r_{t,t+1} \frac{P_t}{P_{t+1}}.$$

In a symmetric equilibrium, and replacing the stochastic discount factor with the complete market equation, the first-order conditions could be rewritten as

$$\begin{aligned}
[p_{j,t}] &: S_t = -\kappa_t (\Upsilon'^{-1})'(1) C_t + \nu_p S_t \pi_t (\pi_t - 1) - \nu_p \beta \mathbb{E}_t r_{t,t+1} S_{t+1} \pi_{t+1} (\pi_{t+1} - 1), \\
[a_{j,t}] &: mc_t = \zeta \kappa_t \Upsilon'^{-1}(1) \frac{C_t}{A_t} + \beta (1-\delta) \mathbb{E}_t r_{t,t+1} mc_{t+1}, \\
[s_{j,t}] &: 1 = \kappa_t + \beta \mathbb{E}_t r_{t,t+1} ((1-\delta) mc_{t+1} - \theta \kappa_{t+1}), \\
[y_{j,t}] &: mc_t = \frac{Q_t}{P_t}, \\
[mc_{j,t}] &: A_t = Y_t + (1-\delta)(A_{t-1} - S_{t-1}), \\
[\kappa_{j,t}] &: S_t = \Upsilon'^{-1}(1) C_t + \theta S_{t-1}.
\end{aligned}$$

Note that $D_t = 1$ in a symmetric equilibrium and that the following conditions hold:

$$\Upsilon'^{-1}(1) = \left(1 + \psi \ln\left(\frac{\eta - 1}{\eta}\right)\right)^{\frac{\eta}{\psi}}, \quad (\Upsilon'^{-1})'(1) = -\eta \left(1 + \psi \ln\left(\frac{\eta - 1}{\eta}\right)\right)^{\frac{\eta}{\psi} - 1}.$$

The key steady-state conditions are

$$\begin{aligned}
S &= -\kappa (\Upsilon'^{-1})'(1) C, \\
(1 - \beta(1-\delta)) mc &= \zeta \kappa \Upsilon'^{-1}(1) \frac{C}{A}, \\
1 &= (1 - \beta\theta)\kappa + \beta(1-\delta) mc, \\
C &= \frac{1-\theta}{\Upsilon'^{-1}(1)} S.
\end{aligned}$$

This implies that

$$\kappa = -\frac{1}{1-\theta}\frac{\Upsilon'^{-1}(1)}{(\Upsilon'^{-1})'(1)} = \frac{1}{\eta(1-\theta)}\left(1+\psi\ln\left(\frac{\eta-1}{\eta}\right)\right),$$

$$mc = \frac{1-(1-\beta\theta)\kappa}{\beta(1-\delta)},$$

$$\zeta = -(1-\beta(1-\delta))mc\frac{(\Upsilon'^{-1})'(1)}{\Upsilon'^{-1}(1)}\frac{A}{S} = \frac{(1-\beta(1-\delta))mc}{\eta}\left(1+\psi\ln\left(\frac{\eta-1}{\eta}\right)\right)^{-1}\frac{A}{S}.$$

Therefore, the optimal pricing condition could be log-linearized as

$$\hat{\pi}_t = \beta\mathbb{E}_t\hat{\pi}_{t+1} - \frac{1}{\nu_p}(\hat{\kappa}_t + \hat{c}_t - \hat{s}_t).$$

The optimal stocking condition could be log-linearized as

$$\widehat{mc}_t = (1-\beta(1-\delta))(\hat{\kappa}_t + \hat{c}_t - \hat{a}_t) + \beta(1-\delta)\mathbb{E}_t(\hat{r}_{t,t+1} + \widehat{mc}_{t+1}).$$

Substituting out $\hat{\kappa}_t$, we get

$$\hat{\pi}_t = \beta\mathbb{E}_t\hat{\pi}_{t+1} + \frac{1}{\nu_p(1-\beta(1-\delta))}[\beta(1-\delta)\mathbb{E}_t(\hat{r}_{t,t+1} + \widehat{mc}_{t+1}) - \widehat{mc}_t] - \frac{1}{\nu_p}(\hat{a}_t - \hat{s}_t).$$

Note that the optimal stocking condition could also be written as

$$\hat{a}_t - \hat{c}_t = \hat{\kappa}_t + \frac{1}{1-\beta(1-\delta)}[\beta(1-\delta)\mathbb{E}_t(\hat{r}_{t,t+1} + \widehat{mc}_{t+1}) - \widehat{mc}_t],$$

meaning that the stock to habit-adjusted sales ratio depends on both the expected marginal cost changes and the shadow value of the sales equation, which is linked to the price markup. In turn, the optimal sales condition could be expressed as

$$\hat{\kappa}_t = \theta\beta\mathbb{E}_t(\hat{r}_{t,t+1} + \hat{\kappa}_{t+1}) - \left[\eta(1-\theta)\left(1+\psi\ln\left(\frac{\eta-1}{\eta}\right)\right)^{-1} - (1-\theta\beta)\right]\mathbb{E}_t(\hat{r}_{t,t+1} + \widehat{mc}_{t+1}).$$

C.3.2 Without inventories

The lagrangian of the retailer without inventories is written as follows:

$$\mathcal{L} = \sum_{t=0}^{\infty} \mathbb{E}_0 \Lambda_{0,t} \Bigg[p_{j,t} s_{j,t} - Q_t y_{j,t} + P_t mc_{j,t} \left\{ y_{j,t} - s_{j,t} \right\}$$
$$+ P_t \kappa_{j,t} \left\{ \Upsilon'^{-1} \left(\frac{p_{j,t}}{P_t} D_t \right) C_t + \theta s_{j,t-1} - s_{j,t} \right\} - \frac{\nu_p}{2} \left(\frac{p_{j,t}}{p_{j,t-1}} - 1 \right)^2 P_t S_t \Bigg].$$

Taking the first order conditions, we get

$$\begin{aligned}
[p_{j,t}] : s_{j,t} &= -\kappa_{j,t} D_t C_t (\Upsilon'^{-1})' \left(\frac{p_{j,t}}{P_t} D_t \right) + \nu_p \frac{P_t S_t}{p_{j,t-1}} \left(\frac{p_{j,t}}{p_{j,t-1}} - 1 \right) \\
&\quad - \nu_p \mathbb{E}_t \frac{\Lambda_{t,t+1} p_{j,t+1} P_{t+1} S_{t+1}}{p_{j,t}^2} \left(\frac{p_{j,t+1}}{p_{j,t}} - 1 \right), \\
[s_{j,t}] : \kappa_{j,t} &= \frac{p_{j,t}}{P_t} - mc_{j,t} + \mathbb{E}_t \frac{\Lambda_{t,t+1} P_{t+1}}{P_t} \theta \kappa_{j,t+1}, \\
[y_{j,t}] : mc_{j,t} &= \frac{Q_t}{P_t}, \\
[mc_{j,t}] : y_{j,t} &= s_{j,t}, \\
[\kappa_{j,t}] : s_{j,t} &= \Upsilon'^{-1} \left(\frac{p_{j,t}}{P_t} D_t \right) C_t + \theta s_{j,t-1}.
\end{aligned}$$

In a symmetric equilibrium, the first-order conditions could be rewritten as

$$\begin{aligned}
[p_{j,t}] : S_t &= -\kappa_t (\Upsilon'^{-1})'(1) C_t + \nu_p S_t \pi_t (\pi_t - 1) - \nu_p \beta \mathbb{E}_t r_{t,t+1} S_{t+1} \pi_{t+1} (\pi_{t+1} - 1), \\
[s_{j,t}] : \kappa_t &= 1 - mc_t + \theta \beta \mathbb{E}_t r_{t,t+1} \kappa_{t+1}, \\
[y_{j,t}] : mc_t &= \frac{Q_t}{P_t}, \\
[mc_{j,t}] : Y_t &= S_t, \\
[\kappa_{j,t}] : S_t &= \Upsilon'^{-1}(1) C_t + \theta S_{t-1}.
\end{aligned}$$

The key steady-state conditions are

$$
\begin{aligned}
S &= -\kappa(\Upsilon'^{-1})'(1)C, \\
1 &= (1-\beta\theta)\kappa + mc, \\
C &= \frac{1-\theta}{\Upsilon'^{-1}(1)}S.
\end{aligned}
$$

This implies that

$$
\begin{aligned}
\kappa = -\frac{1}{1-\theta}\frac{\Upsilon'^{-1}(1)}{(\Upsilon'^{-1})'(1)} &= \frac{1}{\eta(1-\theta)}\left(1+\psi\ln\left(\frac{\eta-1}{\eta}\right)\right), \\
mc &= 1-(1-\beta\theta)\kappa.
\end{aligned}
$$

Therefore, the optimal pricing condition could be log-linearized as

$$
\hat{\pi}_t = \beta\mathbb{E}_t\hat{\pi}_{t+1} - \frac{1}{\nu_p}(\hat{\kappa}_t + \hat{c}_t - \hat{s}_t).
$$

The optimal sales condition could be expressed as

$$
\hat{\kappa}_t = \theta\beta\mathbb{E}_t(\hat{r}_{t,t+1} + \hat{\kappa}_{t+1}) - \left[\eta(1-\theta)\left(1+\psi\ln\left(\frac{\eta-1}{\eta}\right)\right)^{-1} - (1-\theta\beta)\right]\widehat{mc}_t.
$$

D Appendix to Section 5

In this section, we assess the robustness of our results along four dimensions: (i) replacing SPF-based inflation expectations with those from the Michigan Survey; (ii) employing alternative proxies for real marginal cost; (iii) estimating the NKPC with core goods PCE inflation as the dependent variable; and (iv) introducing a nonlinear inventory specification. Finally, we also examine pseudo-out-of-sample performance.

D.1 Specification with Michigan Survey inflation expectations

Our main results are robust to using inflation expectations from the Michigan Survey instead of the SPF. Table D.1 is analogous to Table 3 in the main text but replaces SPF expectations with those from the Michigan Survey. For headline PCE inflation, the Michigan Survey improves the fit of all three NKPC specifications in columns (4)-(6) relative to their SPF-based counterparts, as measured by the adjusted R-squared. Nevertheless, our main results hold: the stock-based NKPC in column (6) delivers the best fit and retains a significantly negative coefficient on the inventory-sales ratio. For goods PCE inflation, the improvement in fit from adding the inventory-sales ratio—comparing column (3) to column (1)—is even larger than in the headline case, as reflected in the adjusted R-squared.

Table D.1: NKPC Estimates for Goods and Headline Inflation (Michigan Expectations)

	Goods PCE Inflation			Headline PCE Inflation		
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged inflation	0.137	0.136	-0.017	0.160	0.147	0.040
	(0.108)	(0.107)	(0.104)	(0.098)	(0.104)	(0.102)
Exp. inflation (Michigan)	1.549***	1.564***	1.250***	0.945***	0.933***	0.810***
	(0.463)	(0.463)	(0.360)	(0.210)	(0.207)	(0.149)
Marginal cost	-0.033			0.090		
	(0.160)			(0.065)		
Exp. marginal cost		-0.029			0.066	
		(0.091)			(0.046)	
Exp. marginal cost growth			0.226			0.212***
			(0.149)			(0.080)
IS ratio			-0.332***			-0.137***
			(0.080)			(0.039)
Constant	-5.256***	-5.285***	-4.048***	-1.687***	1.680***	-1.105**
	(1.687)	(1.703)	(1.341)	(0.644)	(0.659)	(0.494)
Observations	167	167	167	167	167	167
Adjusted R-squared	0.274	0.275	0.425	0.465	0.471	0.574

Notes: Variable definitions are provided in the main text. Expected inflation is from the Michigan Survey. Newey–West standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

D.2 NKPC model fit and forecast performance

Table D.2 reports three model comparison measures: the Akaike (AIC) and Bayesian (BIC) information criteria, which gauge in-sample fit with a penalty for model complexity, and the one-quarter-ahead root mean squared error (RMSE), a pseudo-out-of-sample accuracy measure computed from a recursive regression starting with 1981q3-1995q1 and expanding through 2025q1. For all three metrics, lower values indicate better performance. Across goods and headline inflation, and using either SPF or Michigan inflation expectations, all measures favor the stock-based NKPC.

Table D.2: In-sample Fit and One-quarter-ahead Forecast Performance

	Canonical NKPC	CES-demand NKPC	Stock-based NKPC
Panel A: Goods PCE Inflation – SPF			
AIC	865.98	866.02	811.72
BIC	878.46	878.49	827.31
RMSE	3.73	3.73	3.45
Panel B: Goods PCE Inflation – Michigan			
AIC	835.72	835.63	797.92
BIC	848.20	848.10	813.51
RMSE	3.87	3.88	3.69
Panel C: Headline PCE Inflation – SPF			
AIC	595.83	596.17	544.21
BIC	608.30	608.64	559.80
RMSE	1.72	1.72	1.58
Panel D: Headline PCE Inflation – Michigan			
AIC	554.61	552.73	517.58
BIC	567.08	565.20	533.17
RMSE	1.77	1.74	1.61

Notes: The CES-demand NKPC corresponds to the sales-based specification under CES demand. AIC denotes the Akaike Information Criterion and BIC the Bayesian Information Criterion. RMSE is the one-quarter-ahead root mean squared error, computed from a recursive regression beginning with the sample period 1981q3–1995q1. Lower AIC and BIC values indicate better in-sample fit, while lower RMSE indicates superior out-of-sample performance.

For a formal pseudo-out-of-sample predictive-accuracy comparison between the stock-based and CES-demand NKPCs, we report the Diebold-Mariano (DM) statistics. Again, we re-estimate each specification recursively, starting with 1981q3-1995q and expanding through 2025q1, and generate one-quarter-ahead forecasts. DM statistics are computed from squared forecast errors. Table D.3 reports results for our four specifications, where positive values favor the stock-based NKPC over the CES-demand NKPC.

In the full sample, DM statistics generally favor the stock-based specification, although power is limited given the reduced pseudo-out-of-sample size. By subsample, the stock-based NKPC delivers significantly higher predictive accuracy for goods inflation in the latter period (2010q1–2025q1). For headline inflation, gains are significant in the earlier period (1995q1-2009q4) and less clear thereafter. Overall, the DM tests tend to favor the stock-based NKPC, with weaker power in shorter windows.

Table D.3: Diebold-Mariano Tests: Recursive Pseudo-out-of-sample (One-quarter-ahead)

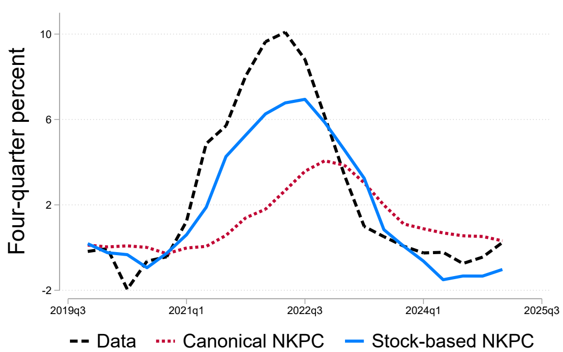
	1995q1-2025q1	1995q1-2009q4	2010q1-2025q1
Panel A: Goods PCE – SPF			
DM statistic	1.234	-0.263	1.373*
Panel B: Goods PCE – Michigan			
DM statistic	1.138	-1.049	1.733**
Panel C: Headline PCE – SPF			
DM statistic	1.172	1.734**	0.683
Panel D: Headline PCE – Michigan			
DM statistic	1.486*	1.810**	1.346*

Notes: Positive values indicate lower squared forecast errors for the stock-based NKPC relative to the CES-demand NKPC. One-quarter-ahead forecasts are generated from recursive estimations starting with 1981q3–1995q1 and expanding through 2025q1. DM statistics are based on quadratic loss differentials. * p<0.10, ** p<0.05, *** p<0.01.

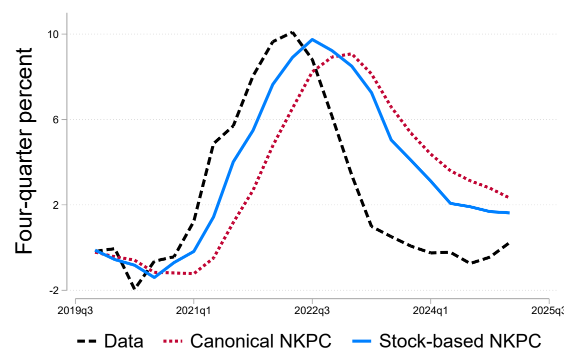
COVID-era pseudo-out-of-sample forecasts. Given the limited power of DM tests, the COVID-era inflation surge provides a useful episode for pseudo-out-of-sample comparisons, since the models are estimated without exposure to this period. Figure D.1 plots one-quarter-ahead pseudo-out-of-sample forecasts against realized goods and headline inflation from 2019q4 onward, using both SPF and Michigan inflation expectations. For comparability with the main text, we show the stock-based and canonical NKPCs (the CES-demand NKPC behaves similarly to the canonical NKPC). The patterns mirror our in-sample results: the stock-based NKPC tracks the data more closely, especially during the COVID-era run-up in goods inflation. In particular, for headline inflation with Michigan expectations, the stock-based NKPC also anticipates an earlier pickup and earlier peak—albeit a lower one than the canonical NKPC—followed by a faster reversal.

Figure D.1: Pseudo-out-of-sample model fit (One-quarter-ahead)

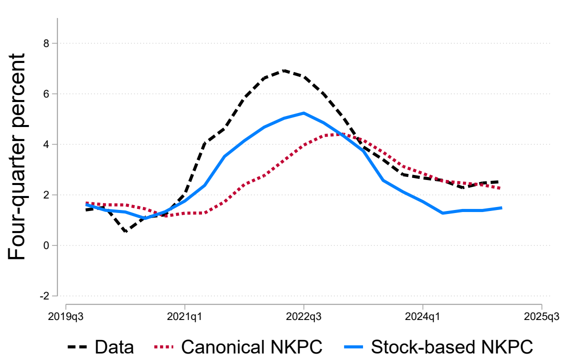
(A) Goods PCE Inflation – SPF



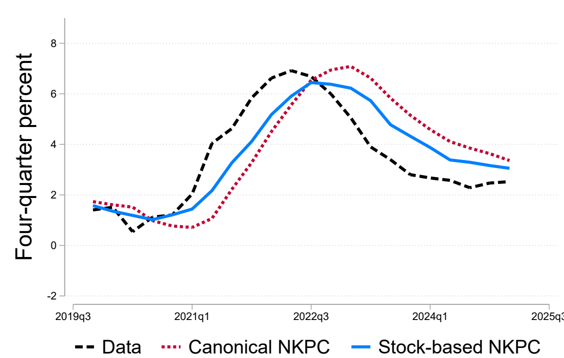
(B) Goods PCE Inflation – Michigan



(C) Headline PCE Inflation – SPF



(D) Headline PCE Inflation – Michigan



Notes: Panels A and B plot one-quarter-ahead pseudo–out-of-sample forecasts for goods PCE inflation using year-ahead SPF (A) and Michigan (B) expectations. Panels C and D show the corresponding forecasts for headline PCE inflation using year-ahead SPF (C) and Michigan (D) expectations.

D.3 Alternative marginal cost proxies

We estimate the canonical NKPC regression with and without the inventory-sales ratio across several commonly used proxies for real marginal cost. Table D.4 reports results using goods PCE inflation, and Table D.5 reports results using headline PCE inflation. In both tables, columns (1) and (2) use the inverse of the unemployment rate gap, constructed as described in the main text; columns (3) and (4) use the labor share gap; and columns (5) and (6) use the unit labor cost gap, with both gap measures constructed using the Hamilton filter. Finally, columns (7) and (8) use the CBO's output gap. Across all four proxies, including the inventory-sales ratio as an observable improves the fit of the NKPC: the adjusted R-squared value in columns (2), (4), (6), and (8), are consistently higher than those in columns (1), (3), (5), and (7), respectively.

Table D.4: NKPC Estimates for Goods PCE Inflation (SPF Expectations)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged inflation	0.342**	0.0223	0.336**	0.0178	0.345***	-0.00727	0.329**	0.0287
	(0.131)	(0.0998)	(0.130)	(0.104)	(0.127)	(0.0933)	(0.132)	(0.102)
Exp. inflation (SPF)	0.369	1.237***	0.451	1.432***	0.395	1.399***	0.323	1.198***
	(0.284)	(0.423)	(0.334)	(0.440)	(0.333)	(0.440)	(0.278)	(0.417)
Unemp. rate gap (inverse)	0.0303	0.269*						
	(0.145)	(0.140)						
Labor share gap			-0.127	0.139				
			(0.115)	(0.106)				
Unit labor cost gap					-0.00943	0.183*		
					(0.135)	(0.0963)		
Output gap (CBO)							0.223	0.245*
							(0.155)	(0.127)
IS ratio gap		-0.452***		-0.473***		-0.469***		-0.432***
		(0.0861)		(0.0856)		(0.0848)		(0.0836)
Constant	-0.282	-2.211**	-0.526	-2.913**	-0.379	-2.794**	-0.0325	-2.167**
	(0.868)	(1.105)	(0.978)	(1.141)	(0.995)	(1.150)	(0.869)	(1.088)
Observations	167	167	164	164	164	164	167	167
Adjusted R-squared	0.130	0.390	0.136	0.395	0.130	0.399	0.144	0.391

Notes: Newey-West standard errors are reported in parentheses. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

Table D.5: NKPC Estimates for Headline PCE Inflation (SPF Expectations)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged inflation	0.455***	0.123	0.458***	0.194	0.459***	0.0841	0.429***	0.140
	(0.135)	(0.117)	(0.131)	(0.122)	(0.125)	(0.105)	(0.139)	(0.122)
Exp. inflation (SPF)	0.321**	0.842***	0.369*	0.863***	0.308*	0.891***	0.316**	0.804***
	(0.160)	(0.203)	(0.188)	(0.239)	(0.171)	(0.208)	(0.159)	(0.199)
Unemp. rate gap (inverse)	0.0744	0.226***						
	(0.0630)	(0.0701)						
Labor share gap			-0.0830	0.0123				
			(0.0550)	(0.0591)				
Unit labor cost gap					0.0431	0.178***		
					(0.0537)	(0.0498)		
Output gap (CBO)							0.149**	0.187***
							(0.0718)	(0.0652)
IS ratio gap		-0.210***		-0.193***		-0.216***		-0.192***
		(0.0431)		(0.0477)		(0.0433)		(0.0413)
Constant	0.461	-0.106	0.256	-0.494	0.424	-0.308	0.566*	-0.103
	(0.313)	(0.431)	(0.373)	(0.495)	(0.364)	(0.465)	(0.325)	(0.424)
Observations	167	167	164	164	164	164	167	167
Adjusted R-squared	0.315	0.533	0.320	0.504	0.312	0.539	0.333	0.530

Notes: Newey-West standard errors are reported in parentheses. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

D.4 Core goods PCE inflation

Table D.6 reports NKPC regression results when using core goods inflation as the dependent variable rather than overall goods inflation. To ensure consistency, we remove food and energy components from both wholesale and retail inventories and sales. Specifically, we exclude groceries, alcoholic beverages, and petroleum from wholesale measures, and drop food and beverage stores from retail inventories and sales as well as gasoline stations from retail sales. Constructing these core-consistent measures requires more detailed category-level data, which are only available beginning in 1992, reducing the sample to 122 observations. Within this sample, our results continue to hold for core goods PCE: the coefficient on the inventory-sales ratio remains negative and statistically significant, and the adjusted R-squared improves markedly for the stock-based NKPC relative to the canonical NKPC.

Table D.6: NKPC Estimates for Core Goods PCE Inflation

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged inflation	0.606***	0.592***	0.330**	0.398***	0.373***	0.256**
	(0.143)	(0.148)	(0.127)	(0.129)	(0.128)	(0.121)
Exp. inflation (SPF)	-0.366	-0.129	0.836			
	(0.320)	(0.326)	(0.522)			
Exp. inflation (Michigan)				0.558***	0.596***	0.442***
				(0.175)	(0.185)	(0.123)
Marginal cost	0.022			-0.053		
	(0.079)			(0.078)		
Exp. marginal cost		-0.031			-0.073*	
		(0.039)			(0.044)	
Exp. marginal cost growth			-0.112			-0.077
			(0.092)			(0.089)
IS ratio			-0.182**			-0.145**
			(0.069)			(0.065)
Constant	0.842	0.250	-2.013	-2.252***	-2.400***	-1.758***
	(0.882)	(0.850)	(1.250)	(0.594)	(0.649)	(0.498)
Observations	122	122	122	122	122	122
Adjusted R-squared	0.338	0.339	0.493	0.415	0.427	0.533

Notes: All the variables are described in the main text. For example, the marginal cost is proxied by the inverse of the unemployment gap and the expected marginal cost is defined as the sum of the expected real interest rate and the expected inverse of the unemployment gap. The expected marginal cost growth is the difference between the expected marginal cost and the marginal cost. Newey–West standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

D.5 Introducing a nonlinear inventory specification

In this section we consider one specific form of nonlinearity in the inventory channel: an interaction between the inventory–sales ratio gap and an indicator for whether the gap is negative or positive. This specification is motivated by the idea that inventory shortages may affect markups differently from inventory surpluses, and thus captures a potentially important asymmetry of interest to the literature. We emphasize, however, that this is only one way of modeling nonlinearities in the NKPC. A fuller exploration of alternative nonlinear specifications is an important question for future research and lies beyond the scope of this paper. Our main contribution is to document robust evidence of a strong linear effect of inventories on inflation dynamics, a relationship that has not been firmly established in the prior literature.

Columns (2) and (5) of Tables D.7 and D.8 report the stock-based NKPC estimates, fitted to goods and headline PCE, respectively, when the regression is augmented with a nonlinear inventory term that interacts the inventory–sales ratio gap with an indicator for whether the gap is negative. The coefficient on the linear inventory-sales ratio gap remains negative in both regressions, consistent with the baseline linear results. The interaction term also enters with a negative sign, suggesting possible nonlinear effects when inventories fall short of trend.

The evidence for such nonlinearity, however, is weak. The nonlinear term is estimated imprecisely, with absolute t-statistics close to or below one, and its inclusion reduces the precision of the linear inventory coefficient, which loses conventional statistical significance. Nevertheless, the linear inventory-sales ratio gap continues to emerge as the primary inventory-related driver of inflation dynamics in these regressions.

To assess whether the weaker significance reflects collinearity with the nonlinear interaction rather than the disappearance of the linear effect, we re-estimate the specification using an interaction term for positive inventory-sales ratio gaps. In columns (3) and (6) of the tables, the linear inventory coefficient remains negative and statistically significant, while the nonlinear interaction is small and insignificant. Unlike the negative-gap specification, the positive-gap interaction does not appear strongly collinear with the linear inventory term in our data, which is why the linear coefficient remains precisely estimated.

These results suggest that the weaker significance in the negative-gap specification reflects multicollinearity, not the absence of the linear inventory channel. Overall, the evidence points to a robust linear effect of inventories on inflation, with only limited and imprecise signs of potential nonlinearities.

Table D.7: Inventory Nonlinearity in Stock-based NKPC (Goods PCE)

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged inflation	0.0473	0.0412	0.0412	-0.0171	-0.0179	-0.0179
	(0.0998)	(0.0909)	(0.0909)	(0.104)	(0.101)	(0.101)
Exp. inflation (SPF)	1.172**	1.119**	1.119**			
	(0.459)	(0.453)	(0.453)			
Exp. inflation (Michigan)				1.250***	1.212***	1.212***
				(0.360)	(0.393)	(0.393)
Exp. marginal cost growth	0.0475	0.106	0.106	0.226	0.255*	0.255*
	(0.166)	(0.140)	(0.140)	(0.149)	(0.137)	(0.137)
IS ratio gap	-0.430***	-0.306	-0.511***	-0.332***	-0.268	-0.379***
	(0.0917)	(0.185)	(0.0768)	(0.0796)	(0.178)	(0.0769)
IS ratio gap < 0		-0.205			-0.111	
		(0.193)			(0.207)	
IS ratio gap > 0			0.205			0.111
			(0.193)			(0.207)
Constant	-2.299**	-2.552**	-2.552**	-4.048***	-4.113***	-4.113***
	(1.158)	(1.161)	(1.161)	(1.341)	(1.267)	(1.267)
Observations	167	167	167	167	167	167
Adjusted R-squared	0.375	0.378	0.378	0.425	0.423	0.423

Notes: Newey-West standard errors are reported in parentheses. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.

TABLE D.8: Inventory Nonlinearity in the Stock-based NKPC for Headline PCE Inflation

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged inflation	0.197	0.192*	0.192*	0.0404	0.0404	0.0404
	(0.120)	(0.112)	(0.112)	(0.102)	(0.102)	(0.102)
Exp. inflation (SPF)	0.665***	0.651***	0.651***			
	(0.225)	(0.226)	(0.226)			
Exp. inflation (Michigan)				0.810***	0.808***	0.808***
				(0.149)	(0.164)	(0.164)
Exp. marginal cost growth	0.0888	0.106	0.106	0.212***	0.213***	0.213***
	(0.0938)	(0.0819)	(0.0819)	(0.0799)	(0.0672)	(0.0672)
IS ratio gap	-0.189***	-0.153*	-0.213***	-0.137***	-0.134	-0.139***
	(0.0475)	(0.0891)	(0.0403)	(0.0393)	(0.0821)	(0.0382)
IS ratio gap < 0		-0.0604			-0.00451	
		(0.0897)			(0.0931)	
IS ratio gap > 0			0.0604			0.00451
			(0.0897)			(0.0931)
Constant	-0.0274	-0.0979	-0.0979	-1.105**	-1.107**	-1.107**
	(0.530)	(0.518)	(0.518)	(0.494)	(0.485)	(0.485)
Observations	167	167	167	167	167	167
Adjusted R-squared	0.500	0.499	0.499	0.574	0.571	0.571

Note: Newey-West standard errors are reported in parentheses. * denotes 10% significance, ** denotes 5% significance, *** denotes 1% significance.