

Inventories, Macroeconomic Risk, and the Cross-Section of Stock Returns

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Abstract

We study how firms' inventory policies shape their exposure to aggregate demand and supply shocks. In a production-based asset pricing model with inventory management, we show that the shadow value of inventories reflects two opposing forces: a cost-smoothing channel that hedges adverse supply shocks by allowing firms to sell from inventory when marginal costs rise, and a stock-out option value that amplifies exposure to demand shocks as inventories become less valuable in low-demand states. This duality implies that inventories can act as either a hedge or a source of risk, depending on the shock. Empirically, firms with higher inventories load positively on demand shocks and negatively on supply shocks, and the resulting inventory premium varies with the prices of these risks. Inventories thus play a central role in transmitting fundamental macroeconomic shocks into asset prices.

JEL Classification Codes: G12, E32, E22, E44, D92, L11.

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1 Introduction

Inventories play an important role in the economy, allowing firms to buffer shocks by decoupling production from sales. Their importance has been underscored by recent disruptions such as the COVID-19 pandemic and the global trade tensions associated with the recent tariff war. When demand is strong, inventories of finished goods enable firms to meet customer needs without costly surges in production. Conversely, when supply conditions deteriorate—for example, due to rising input costs caused by tariffs—inventory buffers allow firms to sustain sales even as production becomes more expensive. Inventories are also quantitatively important: in our sample, they represent roughly 20% of total assets, indicating substantial potential to affect both firm value and risk. Yet, despite their scale and well-documented macroeconomic importance (e.g., [Blinder, 1981](#); [Ramey and West, 1999](#)), we know surprisingly little about how firms’ inventory policies interact with aggregate demand and supply risks to shape the cross-section of expected returns.

In this paper, we study how inventories transmit fundamental macroeconomic shocks into the cross-section of stock returns, both theoretically and empirically. We show that inventory holdings are not merely an operational choice but a critical state variable that governs firms’ cyclical risk exposures and shapes how aggregate fluctuations are priced in financial markets.

Our theoretical contribution is to show that inventories expose firms to two primary and opposing forces. On the one hand, inventories provide a *cost-smoothing* channel: when adverse supply shocks raise marginal production costs, firms with larger inventory buffers can meet demand without increasing production, thereby reducing their sensitivity to supply-driven fluctuations. On the other hand, inventories generate a *stock-out option value*: in high-demand states, firms with ample inventories earn higher revenues by avoiding lost sales (e.g., see [Kahn \(1987\)](#)), amplifying their exposure to demand-driven fluctuations. This duality implies that inventories can act as either a hedge or a source of risk, depending on the nature of the underlying shock.

To formalize these ideas, we augment a standard production-based asset pricing framework (e.g., [Zhang \(2005\)](#)) to incorporate firms’ inventory decisions. Firms produce differentiated goods that are sold through a continuum of retail markets. Each period, before the realization of demand, firms must allocate their inventory across these markets. Because retail demand shocks are i.i.d. and realized only after allocation, firms face the possibility

of a stock-out whenever demand in a given market exceeds the allocated quantity. Any unsold goods are carried forward into the next period, subject to physical depreciation and inventory adjustment costs.

Importantly, firms are exposed to two types of shocks, each of which may contain both aggregate and firm-specific components. A supply shock affects firms' productivity and therefore their marginal costs of production. A demand shock, by contrast, shifts consumers' willingness to purchase a firm's products across all retail markets. This demand disturbance can be interpreted either as a product taste shock (for a firm-level innovation) or as an aggregate force that stimulates demand broadly—such as a monetary policy shock. This shock structure allows inventories to play a dual role. First, inventories enable cost smoothing: firms can increase production when marginal costs are low and rely on stored inventories when marginal costs rise. Second, inventories help firms avoid costly stock-outs, especially when demand for the firm's product—and thus the associated markup—is high.

This dual role of inventories gives rise to an endogenous inventory value (an inventory- q), which captures the shadow value of holding an additional unit of inventories. We show that this value decomposes into two conceptually distinct components: a cost-smoothing value and a stock-out option value. Importantly, these two components load very differently on demand versus supply shocks. The cost-smoothing value is most valuable when marginal costs are high—typically in bad economic times when the price of risk is elevated—implying that inventories hedge against supply risk. By contrast, the stock-out option becomes more valuable in high-demand states, when stock-outs are more likely and markups rise. Because such states occur in good economic times, inventories amplify demand risk. In short, the effect of inventories on firm-level risk depends critically on the source of aggregate risk: inventories hedge supply shocks but heighten exposure to demand shocks.

The model generates two novel empirical predictions. First, firms with high inventory levels should exhibit greater exposure to aggregate demand shocks and lower exposure to aggregate supply shocks relative to low-inventory firms. Second, these differential exposures imply time variation in risk premia across the cross-section. In particular, periods with elevated supply-shock risk should reduce the expected return of high-inventory firms (as inventories hedge supply disturbances), whereas periods with elevated demand-shock risk should increase the expected return of high-inventory firms (as inventories amplify exposure to demand fluctuations). Taken together, these predictions also imply that the nature of realized

aggregate shocks of demand versus supply and the prevailing source of macroeconomic risk can be inferred from the relative stock market performance of firms sorted on their inventory levels.

We then test these predictions in the data. First, we document unconditional return patterns using portfolio sorts and [Fama and MacBeth \(1973\)](#) regressions, showing that firms with higher inventory-to-sales ratios earn significantly lower average returns. These results are both statistically and economically meaningful: high-inventory firms earn approximately 2.3% lower annual returns than low-inventory firms. The findings are robust to controlling for industry fixed effects, to using either value- or equal-weighted portfolios, and to adjusting for standard asset pricing factors. Taken together, these patterns suggest that supply shocks account for a larger share of priced risk relative to demand shocks. Interestingly, the empirical magnitudes align closely with our calibrated model, in which the cost-smoothing channel also dominates the stock-out option value, causing high-inventory firms to command a lower equity risk premium.

Next, we test the model’s conditional predictions. We measure aggregate supply and demand shocks using revisions in professional forecasts, following [Bekaert et al. \(2025\)](#). We then regress the return on the Low-minus-High (LMH) inventory portfolio on these estimated aggregate shocks. Consistent with the model, we find that high-inventory firms are significantly more exposed to demand shocks but less exposed to supply shocks than low-inventory firms. This pattern is robust across alternative specifications and remains strong after controlling for the Fama–French five-factor model. Overall, these results provide compelling evidence that inventory holdings fundamentally shape firms’ exposures (i.e., their betas) to supply versus demand shocks.

We further estimate the prices of demand and supply risk using a two-pass regression procedure (e.g., [Cochrane, 2005](#)). We show that the LMH premium tends to be higher in periods when supply risk is more highly priced, but lower when demand risk commands a higher premium. These findings indicate that inventories not only affect firms’ shock exposures but also their expected risk premia, and that inventories play a central role in transmitting supply and demand risks into the cross-section of returns.

Related Literature. The cost-smoothing and stock-out-avoidance motives for inventory accumulation are well documented in the macroeconomic literature (e.g., [Eichenbaum, 1989](#);

Blinder and Maccini, 1991; Bils and Kahn, 2000). More recent work by Bils and Kahn (2000) and Kryvtsov and Midrigan (2012) shows that the stock-out-avoidance motive, and the associated markup dynamics, play a central role in explaining the time-series variation in the aggregate inventory-to-sales ratio. Separately, Khan and Thomas (2007) and Bachmann and Bayer (2013) study the classical (s, S) inventory model and show that the lumpy nature of inventory investment amplifies business-cycle fluctuations, helping to account for the high volatility of inventory investment. Crouzet and Oh (2016) quantifies the contribution of news shocks to business cycles by examining the dynamic comovement between sales and finished-goods inventories. Our paper builds on this literature by deriving a market value of inventories—an inventory- q —and examining the cross-sectional and time-series asset-pricing implications of inventory accumulation guided by these motives. Crucially, we distinguish between two distinct sources of aggregate fluctuations—demand versus supply—and show that inventories load very differently on these two fundamental shocks.

In this aspect, our study contributes to the asset-pricing literature that uses the cross-section and time-series of returns to infer the fundamental sources of aggregate fluctuations. This research agenda has identified a wide range of aggregate shocks as priced drivers of asset returns, including productivity shocks (e.g., Croce, 2014; Favilukis and Lin, 2013; Kung and Schmid, 2015), investment-specific technology shocks (e.g., Kogan and Papanikolaou, 2014; Knesl, 2018), and fiscal or monetary policy shocks (e.g., Belo and Yu, 2013; Croce et al., 2019; Bretscher et al., 2020a). Other work highlights the role of uncertainty shocks (e.g., Bretscher et al., 2020b), external financing conditions (e.g., Belo et al., 2019), and variation in capital depreciation (e.g., Ai et al., 2025; Grigoris and Segal, 2024). Corhay, Li, and Tong (2025) further documents the asset-pricing effects of exogenous variation in aggregate markups. We build on this literature by showing that portfolios sorted on firms’ inventory-to-sales ratios provide a novel cross-sectional moment for distinguishing between supply-driven and demand-driven aggregate risks. In particular, the behavior of the Low-minus-High inventory portfolio offers a market-based indicator of whether aggregate fluctuations are predominantly shaped by supply-side or demand-side forces, thereby introducing a new empirical approach for testing competing business-cycle theories.

The marginal cost-smoothing motive and the incentive to avoid stock-outs also connect our analysis to a growing finance literature studying how industrial organization shapes asset prices in settings with production and strategic interaction (e.g., Aguerrevere, 2009;

Bustamante and Donangelo, 2017; Corhay et al., 2020; Dou et al., 2021; Doshi and Kumar, 2021).¹ In these models, market power matters for asset prices because it amplifies firms’ exposure to aggregate productivity risk. Our paper contributes a novel mechanism: firms endogenize their price-setting decisions through inventory management, driven jointly by marginal cost–smoothing and stock-out–avoidance incentives. We show that accounting for the joint dynamics of inventories and markups has important asset-pricing implications that are absent from existing models.

Finally, this paper contributes to the production-based asset pricing literature that links real frictions to the cross-section of expected returns. For instance, Zhang (2005) explains the value premium within a q -theory framework, while Donangelo, Gourio, Kehrig, and Palacios (2019) relate firm-level labor share to equity returns. Herskovic, Kind, and Kung (2018) study the low-frequency comovement between value and size premiums using a standard q -theory model, and Kuehn, Simutin, and Wang (2017) establish a connection between firms’ exposures to labor market conditions and stock returns. Kuehn and Schmid (2014) extend the q -theory framework to corporate bond pricing, and Eisfeldt and Papanikolaou (2013) incorporate organizational capital to examine its effects on stock returns. Grigoris et al. (2022) examine trade credit and uncertainty (Grigoris and Segal (2021)) within supply chain networks and how it is related to firms’ risks and returns. Most closely related to our setting, Belo and Lin (2012) and Jones and Tuzel (2013) show that inventory growth predicts the cross-section of stock returns. Our paper is novel in that it decomposes the risks associated with inventory holdings into supply- versus demand-driven components and demonstrates that the asset-pricing implications of inventories depend critically on the underlying source of aggregate risk. Importantly, we show that this mechanism provides a new and complementary channel: our results remain robust even after controlling for inventory growth, indicating that the level of inventories captures variation in risk exposures that is distinct from the variation explained by changes in inventories.

¹For example, Corhay (2017), Chen et al. (2020), and Dou et al. (2021) incorporate default risk and show that credit risk is central for understanding the asset-pricing implications of product-market competition. Clara et al. (2021) analyzes the role of multi-product firms.

2 Model

This section develops a production-based model with inventory management. The economy features three interrelated sectors: (i) a production sector in which firms produce differentiated goods, (ii) a distribution sector that retails these goods to consumers across segmented markets, and (iii) a final consumption sector that aggregates the consumption of these goods subject to demand shocks. Idiosyncratic and aggregate shocks to production costs, combined with frictions in the distribution of goods, create a motive for inventory accumulation.

2.1 Final Consumption and Distribution Sectors

We begin by describing the consumption and distribution sectors of the economy. Figure 1 provides a visual representation with two representative goods, 1 and 2, and two local markets, a and b , to illustrate the key flows and segmentation.

2.1.1 Local and Final Consumption

Consumption is segmented across a continuum of local markets indexed by $j \in [0, 1]$. Local consumption in market j , denoted $Y_t(j)$, is a CES aggregate over the consumption of differentiated products supplied by a continuum of firms $i \in [0, 1]$:

$$Y_t(j) = \left(\int_0^1 v_{it}(j)^{\frac{1}{\eta}} Y_{it}(j)^{\frac{\eta-1}{\eta}} di \right)^{\frac{\eta}{\eta-1}}, \quad (1)$$

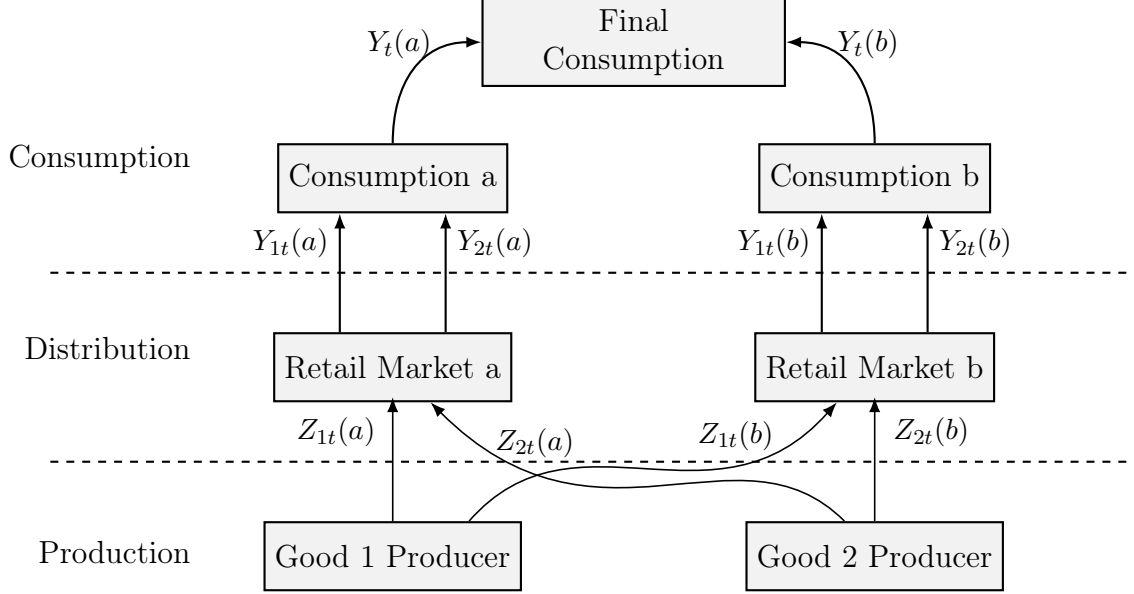
where $\eta > 1$ is the elasticity of substitution across products. A higher value of η implies that products are closer substitutes and hence exhibit weaker differentiation.

Demand in each local market is subject to idiosyncratic shocks $v_{it}(j)$, which are i.i.d. across products and markets. These shocks capture, in reduced form, fluctuations in local tastes, search frictions, and other market-specific conditions affecting the relative appeal of each product. We assume $\log(v_{it}(j)) \sim \mathcal{N}(\mu_{vit}, \sigma_v^2)$, and denote the associated cumulative distribution function by $F_{it}(\cdot)$. The distributional form and parameters are common knowledge.

The time-varying mean μ_{vit} represents product-level demand shifts that are common

FIGURE 1

Diagram of the flow of goods in the economy.



This diagram illustrates the flow of goods from producers to retail markets and final consumption, shown here for two goods (1 and 2) and two local markets (a and b). Each producer allocates a quantity $Z_{it}(j)$ of its good i to market j at the start of the period, before demand is realized. Local demand for good i in market j is denoted $Y_{it}(j)$. If $Y_{it}(j) > Z_{it}(j)$, the retailer experiences a stock-out and sales are capped at $Z_{it}(j)$.

across all markets. We assume μ_{vit} has both an aggregate and firm-specific component:

$$\mu_{vit} = \bar{\mu}_v + \varphi_t + s_{it}, \quad (2)$$

where $\varphi_t = \rho_\phi \varphi_{t-1} + \sigma_\phi \varepsilon_{\varphi t}$, $\varepsilon_{\varphi t} \sim \mathcal{N}(0, 1)$ and $s_{it} = \rho_s s_{it-1} + \sigma_s \varepsilon_{sit}$, $\varepsilon_{sit} \sim \mathcal{N}(0, 1)$. Here, $\bar{\mu}_v$ is the steady-state mean demand shifter, φ_t is an aggregate (priced) demand shock that affects all firms in the economy, and s_{it} is a firm-specific shock. Firms that experience different histories of ε_{sit} will face different expected levels of demand, generating heterogeneity in sales, inventory decisions, revenues, and asset prices across firms in equilibrium. These demand shocks are the key source of cross-sectional heterogeneity in the model.

The aggregate final consumption good, Y_t , is obtained by aggregating local consumption across all markets. This ensures that each market is infinitesimally small so that the law of

large numbers applies:

$$Y_t = \int_0^1 Y_t(j) dj. \quad (3)$$

2.1.2 Distribution

Local consumption in market j is obtained from its own retail market $j \in [0, 1]$. At the beginning of each period, before demand shocks are realized, each firm allocates a stock of its product to each market, denoted $Z_{it}(j)$. After the demand shocks materialize, sales in market j cannot exceed the allocated stock $Z_{it}(j)$; if realized demand is higher, the retailer experiences a stock-out and sales are capped at $Z_{it}(j)$. At the end of the period, any unsold inventory is returned to the firm, which can then reallocate the remaining stock across markets at the start of the next period.

Since firms must allocate $Z_{it}(j)$ before observing demand, and because within-period reallocation is not possible, firms face stock-out risk. This risk creates a precautionary motive to hold inventory in equilibrium.

2.1.3 Equilibrium Product Demand

We now derive equilibrium product demand by solving the joint problem of the final and local consumption sectors. Specifically, the objective is to choose $\{Y_{it}(j)\}_{i,j \in [0,1]}$ to minimize total expenditure subject to (i) an aggregate final-consumption target Y_t^* and (ii) market-specific stock-out constraints. Mathematically,

$$\min_{\{Y_{it}(j)\}} \int_0^1 \int_0^1 P_{it} Y_{it}(j) dj di \quad (4)$$

$$\text{s.t.} \quad Y_t^* = \int_0^1 \left(\int_0^1 v_{it}(j)^{\frac{1}{\eta}} Y_{it}(j)^{\frac{\eta-1}{\eta}} di \right)^{\frac{\eta}{\eta-1}} dj, \quad (5)$$

$$Y_{it}(j) \leq Z_{it}(j), \quad \forall i, j. \quad (6)$$

Here, P_{it} is the price of product i , chosen before local demand shocks are realized. Constraint (5) enforces the aggregate final consumption target Y_t^* , and (6) imposes the stock-out condition that sales in market j cannot exceed the quantity allocated to that market.

Solving the problem yields the local demand schedule

$$Y_{it}(j) = v_{it}(j) \left(\frac{P_{it} + \Lambda_{it}^Z(j)}{P_t^Y} \right)^{-\eta} Y_t(j), \quad (7)$$

where $\Lambda_{it}^Z(j) \geq 0$ is the Lagrange multiplier on the stock-out constraint (6) and P_t^Y is the aggregate price index associated with the aggregator in (5). Note that $P_{it} + \Lambda_{it}^Z(j)$ captures the “effective price” of good i in market j and accounts for the shadow value of the stock-out: when the constraint binds, $\Lambda_{it}^Z(j) > 0$ and demand is constrained.

We can define the stock-out threshold $v_{it}^*(j)$ as the realization of $v_{it}(j)$ at which the stock-out constraint is just binding, with $\Lambda_{it}^Z(j) = 0$:

$$v_{it}^*(j) = \frac{Z_{it}(j)}{Y_t(j)} \left(\frac{P_{it}}{P_t^Y} \right)^\eta. \quad (8)$$

Using (8), the demand for good i in market j takes the piecewise form

$$Y_{it}(j) = \begin{cases} v_{it}(j) \left(\frac{P_{it}}{P_t^Y} \right)^{-\eta} Y_t(j), & \text{if } v_{it}(j) \leq v_{it}^*(j), \\ Z_{it}(j), & \text{if } v_{it}(j) > v_{it}^*(j). \end{cases} \quad (9)$$

Firm Product Demand. Aggregating across markets j and applying the law of large numbers delivers total demand for firm i ’s product:

$$Y_{it} = \int_0^1 Y_{it}(j) dj \quad (10)$$

$$= \int_{v \leq v_{it}^*(j)} v_{it}(j) \left(\frac{P_{it}}{P_t^Y} \right)^{-\eta} Y_t(j) dF_{it}(v) + \int_{v > v_{it}^*(j)} Z_{it}(j) dF_{it}(v). \quad (11)$$

Imposing symmetry across retail markets (and thus dropping j) yields firm i ’s demand:

$$Y_{it} = \left(\frac{P_{it}}{P_t^Y} \right)^{-\eta} Y_t \int_0^{v_{it}^*} v dF_{it}(v) + (1 - F_{it}(v_{it}^*)) Z_{it}. \quad (12)$$

To build intuition for expression (12), consider first the case in which the firm never

experiences a stock-out, i.e., $v_{it}^* = +\infty$. In this case, demand reduces to the standard CES form, where the elasticity of demand is constant and determined solely by the substitution parameter η . The mean component μ_{vit} acts as a product-level demand shifter:

$$Y_{it}^{\text{no stock-out}} = \mu_{vit} \left(\frac{P_{it}}{P_t^Y} \right)^{-\eta} Y_t. \quad (13)$$

When stock-out risk is present (i.e., v_{it}^* is finite), the demand schedule has a kink: once the realized demand shock exceeds the threshold v_{it}^* , sales are capped at the allocated quantity Z_{it} . In this region, any increases in prices do not translate into lower quantities sold, and the firm's demand becomes locally inelastic. As a result, the effective elasticity of demand depends on the likelihood of stock-out events. When $F_{it}(v_{it}^*)$ is small—that is, when the probability of $v_{it}(j) > v_{it}^*$ is high—firms face more inelastic demand. This mechanism plays a central role in jointly shaping firms' pricing and inventory decisions.

Aggregate Final Consumption. Using symmetry across local retail markets, let there be n firm types, each with mass $1/n$ on the unit interval; the CES aggregator for the final good is:

$$Y_t = \left(\frac{1}{n} \sum_{i=1}^n \left[Y_{it}^{\frac{\eta-1}{\eta}} \int_0^{v_{it}^*} v^{\frac{1}{\eta}} dF_{it}(v) + Z_{it}^{\frac{\eta-1}{\eta}} \int_{v_{it}^*}^{\infty} v^{\frac{1}{\eta}} dF_{it}(v) \right] \right)^{\frac{\eta}{\eta-1}}. \quad (14)$$

2.2 Production Sector

We now turn to the production sector of the economy, which is populated by a continuum of producers indexed by $i \in [0, 1]$.

2.2.1 Technology

Each firm produces its product using a Cobb–Douglas production technology. Output, X_{it} , is produced using pre-installed capital K_{it} and fully flexible labor L_{it} :

$$X_{it} = [(A_t L_{it})^{1-\alpha} K_{it}^\alpha]^\kappa, \quad (15)$$

where α is the capital share and κ governs returns to scale. Aggregate productivity A_t follows an AR(1) process in logs:

$$\ln(A_t) = (1 - \rho_a) \ln(\bar{A}) + \rho_a \ln(A_{t-1}) + \sigma_a \varepsilon_{at}, \quad \varepsilon_{at} \sim \mathcal{N}(0, 1). \quad (16)$$

Labor is hired competitively at wage rate W_t . Capital accumulates through investment I_{it} and becomes productive in the following period. The law of motion for capital is:

$$K_{it+1} = (1 - \delta_K) K_{it} + I_{it}, \quad (17)$$

where δ_K is the depreciation rate. Investment is subject to quadratic adjustment costs,

$$H_K(I_{it}, K_{it}) = \frac{\xi_K}{2} \left(\frac{I_{it}}{K_{it}} - \delta_K \right)^2 K_{it}, \quad (18)$$

which are homogeneous of degree one in both capital and investment, with $\xi_K \geq 0$ determining the magnitude of the adjustment cost.

2.2.2 Distribution and Inventory

At the beginning of each period, the firm chooses how much of its product to allocate to each local retail market. Because this allocation occurs before demand shocks are realized, all markets are ex ante identical from the firm's perspective. As a result, the optimal allocation is symmetric across markets, and we drop the market index j when deciding on the allocation.

The total amount of product available for sale across retail markets, Z_{it} , comes from two sources: current production and existing inventories. Specifically,

$$Z_{it} = X_{it} + N_{it}, \quad (19)$$

where X_{it} denotes current output and N_{it} is the stock of inventories carried into period t .

All unsold goods are returned to the firm at the end of the period and become inventories available for the following period. Inventory therefore evolves according to

$$N_{it+1} = (1 - \delta_N) (Z_{it} - Y_{it}), \quad (20)$$

where δ_N is the depreciation rate of inventory. This parameter captures all economic costs associated with holding inventories, including physical depreciation, obsolescence, spoilage, and storage costs. Substituting the expression for Y_{it} from (12) into the inventory law of motion, we obtain:

$$N_{it+1} = (1 - \delta_N) \left[F_{it}(v_{it}^*) Z_{it} - \left(\frac{P_{it}}{P_t^Y} \right)^{-\eta} Y_t \int_0^{v_{it}^*} v dF_{it}(v) \right]. \quad (21)$$

Inventory adjustment is costly. We assume that changes in the inventory stock incur a quadratic adjustment cost,

$$H_N(N_{it+1}, N_{it}) = \frac{\xi_N}{2} \left(\frac{N_{it+1}}{N_{it}} - 1 \right)^2 N_{it}, \quad (22)$$

where $\xi_N \geq 0$ is the adjustment-cost parameter. This term captures the idea that rapidly expanding or contracting inventories involves operational and managerial frictions, such as warehouse reorganization, logistical delays, and coordination costs. In equilibrium, these adjustment costs smooth inventory dynamics over time, consistent with empirical patterns in the data.

2.2.3 Pricing

Firms set prices P_{it} before observing the realization of local demand shocks. Price adjustments are subject to Rotemberg-type quadratic adjustment costs (Rotemberg, 1982):

$$H_P(P_{it}, P_{it-1}) = \frac{\xi_P}{2} \left(\frac{P_{it}}{P_{it-1}} - 1 \right)^2 Y_t, \quad (23)$$

where $\xi_P \geq 0$ controls the degree of price stickiness and Y_t denotes aggregate output.

2.2.4 Producer Problem

The firm's real dividend is defined as total revenue net of labor costs, investment expenditures, adjustment costs, and fixed operating costs:

$$D_{it} = P_{it}Y_{it} - W_tL_{it} - I_{it} - H_K(I_{it}, K_{it}) - H_N(N_{it+1}, N_{it}) - H_P(P_{it}, P_{it-1}) - fK_{it}, \quad (24)$$

where f is a fixed operating cost proportional to firm size (captured by K_{it}).

The firm chooses prices P_{it} , next-period inventories N_{it+1} , investment I_{it} , next-period capital K_{it+1} , and labor input L_{it} to maximize the present value of dividends. Let M_{t+1} denote the exogenously specified stochastic discount factor. The firm's dynamic program is

$$V_{it} = \max_{\{P_{it}, X_{it}, N_{it+1}, I_{it}, K_{it+1}, L_{it}\}} \{D_{it} + \mathbb{E}_t [M_{t+1} V_{it+1}]\}, \quad (25)$$

subject to the demand function (12), the production technology (15), capital accumulation (17), and inventory evolution (21).

We denote by λ_{it}^X , λ_{it}^K , and λ_{it}^N the Lagrange multipliers associated with the production technology constraint, the capital accumulation equation, and the inventory accumulation equation, respectively. A detailed derivation of the firm's problem is provided in the Appendix.

Labor. The optimality condition for labor equates the marginal product of labor to the real wage. Using the production technology (15), the associated real marginal cost of production, λ_{it}^X , can be expressed as:

$$\lambda_{it}^X = \frac{W_t}{\kappa(1 - \alpha)X_{it}/L_{it}}. \quad (26)$$

Output. The optimality condition for production is obtained by taking the FOC with respect to X_{it} :

$$\lambda_{it}^X = (1 - F_{it}(v_{it}^*)) P_{it} + F_{it}(v_{it}^*) (1 - \delta_N) \lambda_{it}^N. \quad (27)$$

This condition equates the marginal cost of producing one additional unit of output, λ_{it}^X , to its expected marginal benefit. With probability $1 - F_{it}(v_{it}^*)$, the firm experiences a stock-out and the extra unit is sold at price P_{it} . With probability $F_{it}(v_{it}^*)$, the unit is not immediately sold and instead adds to inventories, yielding continuation value $(1 - \delta_N) \lambda_{it}^N$ after inventory depreciation.

This expression highlights a key departure from standard models: the value of an additional unit of output depends not only on current profitability, but also on the likelihood of stock-outs and the shadow value of inventories. As we show later, both of these compo-

nents depend on expectations of future demand conditions and marginal costs, introducing a forward-looking “inventory option value” component into production decisions.

Inventory. The optimality condition for inventory is obtained by taking the FOC with respect to N_{it+1} :

$$\lambda_{it}^N + \xi_N \left(\frac{N_{it+1}}{N_{it}} - 1 \right) = \quad (28)$$

$$E_t \left[M_{t+1} \left(\underbrace{(1 - F_{it+1}(v_{it+1}^*))P_{it+1} + F_{it+1}(v_{it+1}^*)(1 - \delta_N)\lambda_{it+1}^N}_{\lambda_{it+1}^X} + \frac{\xi_N}{2} \left(\frac{N_{it+2}^2}{N_{it+1}^2} - 1 \right) \right) \right].$$

This condition links the shadow value of inventories today, λ_{it}^N , to the marginal production cost in the future. Using (27), we can rewrite the continuation value term as proportional to λ_{it+1}^X , implying that inventories serve as a buffer that allows firms to substitute away from costly future production. When firms expect higher future marginal costs, λ_{it+1}^X rises, which raises the value of carrying inventories today. Adjustment costs, governed by ξ_N , limit how quickly firms can scale inventories and thereby generate smooth inventory dynamics.

Product Price. The firm’s optimal pricing condition can be written as:

$$P_{it} = \frac{\epsilon_{it}}{\epsilon_{it} - F_{it}(v_{it}^*)} \lambda_{it}^X + \hat{\phi}_{it}, \quad (29)$$

where

$$\epsilon_{it} = \frac{\eta \int_0^{v_{it}^*} v dF_{it}(v)}{\int_0^{v_{it}^*} v dF_{it}(v) + (1 - F_{it}(v_{it}^*)) v_{it}^*} \quad (30)$$

is the effective price elasticity of demand. The key departure from the standard CES case is that stock-out risk makes demand less elastic: when $F_{it}(v_{it}^*)$ is small (i.e., stock-outs are more likely), the elasticity ϵ_{it} falls, increasing the markup of price over marginal cost λ_{it}^X .

The term $\hat{\phi}_{it}$ captures the effect of Rotemberg price adjustment costs on the firm's pricing decision.²

In the absence of stock-out risk and inventory frictions (so that $F_{it}(v_{it}^*) = 1$), the pricing rule collapses to the standard constant-markup expression:

$$P_{it} = \frac{\eta}{\eta - 1} \lambda_{it}^X + \hat{\phi}_{it}, \quad (31)$$

as in a sticky-price CES demand environment. Thus, in our framework, variation in demand conditions and the likelihood of stock-outs generate time-varying markups as in [Kryvtsov and Midrigan, 2012](#).

Investment. The optimal investment choice follows a standard investment Euler equation:

$$\lambda_{it}^K = \mathbb{E}_t \left[M_{t+1} \left(\underbrace{\kappa \alpha \lambda_{it+1}^X \frac{X_{it+1}}{K_{it+1}}}_{R_{it+1}^K} + (1 - \delta_K) \lambda_{it+1}^K + \frac{\xi_K}{2} \left(\frac{I_{it+1}^2}{K_{it+1}^2} - \delta_K^2 \right) \right) \right], \quad (32)$$

$$\lambda_{it}^K = 1 + \xi_K \left(\frac{I_{it}}{K_{it}} - \delta_K \right), \quad (33)$$

where λ_{it}^K is the shadow value of installed capital (marginal q). The term R_{it+1}^K denotes the marginal return to capital which depends on the marginal product of capital scaled by the marginal cost of production.

The firm equates the current marginal value of capital λ_{it}^K , to the discounted expected payoff from holding an additional unit of capital accounting for its future marginal product, depreciation, and future adjustment costs. Because λ_{it+1}^X enters R_{it+1}^K , and λ_{it+1}^X depends on the firm's inventory and stock-out conditions (see (27)), inventory decisions directly affect the return to capital and, therefore, investment. In equilibrium, inventories, production, and investment are jointly determined.

²Formally, $\hat{\phi}_{it} \equiv -\xi_P P_{it} \left(\frac{P_{it}}{P_{it-1}} - 1 \right) \frac{Y_t}{P_{it-1}} + \xi_P \mathbb{E}_t \left[M_{t+1} P_{it+1} \left(\frac{P_{it+1}}{P_{it}} - 1 \right) \frac{Y_{t+1}}{P_{it}} \right]$.

2.3 Aggregate Processes and Equilibrium

Our model focuses on cross-sectional differences across firms and is therefore analyzed in partial equilibrium. To close the model we specify the aggregate processes governing factor and risk prices.

Pricing Kernel. The pricing kernel M_{t+1} is specified as:

$$\log M_{t+1} = \log \beta - \gamma_a \varepsilon_{at+1} - \gamma_\phi \varepsilon_{\phi t+1} - \frac{1}{2} \gamma_a^2 \sigma_a^2 - \frac{1}{2} \gamma_\phi^2 \sigma_\phi^2, \quad (34)$$

where β is the discount factor and $\gamma_a, \gamma_\phi > 0$ are the prices of aggregate productivity and demand risk, respectively. A higher γ implies that marginal utility rises more sharply in downturns (i.e., when ε_{at+1} is low), which generates a positive price of aggregate productivity risk.

Labor Market. Wages are assumed to be constant, $W_t = \bar{W}$, where $\bar{W}$ denotes the steady-state real wage. Aggregate labor supply is normalized to one.

Equilibrium. We restrict attention to a symmetric equilibrium across local retail markets, so that all markets are ex ante identical and the j -index can be suppressed. Because firms allocate goods to markets before the realization of idiosyncratic demand shocks, and because there is a continuum of markets, the law of large numbers implies that firm decisions depend only on the distribution of shocks and not on individual realizations. Thus, demand uncertainty affects firms only through the expected frequency of stock-out events, which is summarized in the stock-out threshold v_{it}^* and the associated distributional objects $(F_{it}, \int_0^{v_{it}^*} v dF_{it}(v))$. This greatly simplifies the computation of equilibrium policies.

Finally, the labor market clears at all dates:

$$\int_0^1 L_{it} di = 1. \quad (35)$$

3 Firm Value Decomposition and Asset Pricing

To understand how inventories contribute to firm valuation and risk, we decompose the ex-dividend value of the firm into three components: (i) the market value of inventories, (ii) the market value of installed capital, and (iii) the present value of rents arising from imperfect competition. The latter two components are standard in production-based models with market power (e.g., [Corhay et al., 2025](#)), whereas the first term—the value of inventories—is specific to our setting. As we show below, inventories play a central role in shaping cross-sectional differences in expected returns because their valuation loads differentially on demand versus supply shocks.

To highlight the economic mechanisms most transparently, we first present the decomposition in the case without adjustment costs in Proposition 1.³ The full derivation and expression with adjustment costs is provided in the Appendix.

Proposition 1. *In the absence of adjustment costs, the ex-dividend value of a producer satisfies*

$$V_{it} - D_{it} = \lambda_{it}^N N_{it+1} + \lambda_{it}^K K_{it+1} + V_{it}^{rents}, \quad (36)$$

where:

(a) $\lambda_{it}^N N_{it+1}$ is the market value of inventories:

$$\lambda_{it}^N N_{it+1} = E_t [M_{t+1} (D_{it+1}^N + \lambda_{it+1}^N N_{it+2})], \quad (37)$$

$$D_{it}^N = (1 - F_{it}(v_{it}^*)) (P_{it} - (1 - \delta_N) \lambda_{it}^N) N_{it} - \lambda_{it}^N (1 - \delta_N) (X_{it} - Y_{it}). \quad (38)$$

(b) $\lambda_{it}^K K_{it+1}$ is the market value of installed capital:

$$\lambda_{it}^K K_{it+1} = E_t [M_{t+1} (D_{it+1}^K + \lambda_{it+1}^K K_{it+2})], \quad (39)$$

$$D_{it}^K = R_{it}^K K_{it} - I_{it}. \quad (40)$$

³Adjustment costs primarily help match dynamic moments in the data. The key economic intuition and risk transmission channels remain unchanged.

(c) V_{it}^{rents} is the (ex-dividend) present discounted value of rents, net of fixed costs:

$$V_{it}^{rents} = E_t [M_{t+1}(D_{it+1}^P + V_{it+1}^P)], \quad (41)$$

$$D_{it}^{rents} = \frac{1}{\epsilon_{it} - 1} \lambda_{it}^N (1 - \delta_N) P_{it}^{-\eta} Y_t \int_0^{v_{it}^*} v dF_{it}(v) + (1 - \kappa) \lambda_{it}^X X_{it} - f K_{it}. \quad (42)$$

The value of inventories stems from two sources: (i) a *stock-out option* and (ii) a *cost-smoothing* value. The first component arises because inventories allow the firm to make sales in high-demand states in which stock-outs would otherwise occur. This is captured by the first term in Equation (38), which applies with probability $(1 - F_{it}(v_{it}^*))$. In those states, the firm sells a unit of inventory at price P_{it} , but forgoes the continuation value of carrying that unit into the next period, $(1 - \delta_N) \lambda_{it}^N$. The stock-out option value is therefore especially large when demand or markups are elevated, since the marginal revenue from selling an additional unit is highest in those states.

As we show below, positive aggregate demand shocks ($\varepsilon_{\varphi t} > 0$) raise both the probability of stock-outs and the markup, and this effect is amplified for firms holding larger inventories. As a result, high-inventory firms earn relatively more revenue in high-demand states, which increases their exposure to demand fluctuations and raises their demand-shock betas. Because the price of risk associated with demand shocks is positive, firms with higher inventory positions command a higher demand-driven risk premium in equilibrium.

The second component reflects the role of inventories in smoothing marginal production costs over time. When current output X_{it} is temporarily low—for example, following an adverse productivity shock—firms can still meet demand by drawing down inventories, allowing sales Y_{it} to exceed current production. This dampens fluctuations in cash flow and reduces exposure to states in which marginal costs are high. In this sense, inventories provide a hedge against adverse supply conditions. Consequently, firms with larger inventory positions exhibit lower exposure to productivity shocks. Since the price of risk associated with productivity shocks is positive, this hedge component lowers the supply-driven risk premium of high-inventory firms in equilibrium.

The value of installed capital follows the standard q -theoretic formulation familiar from investment-based production models. The present value of rents arises from two sources: market power (markups) and deviations from constant returns to scale. In the special case

where production exhibits constant returns to scale ($\kappa = 1$) and the product market is perfectly competitive ($\eta \rightarrow \infty$), both sources of rents vanish, and therefore the value of the rent claim (abstracting from fixed operating costs) reduces to zero.

4 Quantitative Analysis

This section presents a quantitative evaluation of the model to assess the importance of inventories as a determinant of firm risk and to generate empirical predictions to be tested in the data.

4.1 Calibration and Model Fit

4.1.1 Calibration

We begin by describing the calibration of the benchmark model. All parameter values are reported in Table 1. Panel A summarizes the SDF parameters. The prices of TFP and demand shocks, γ_a and γ_ϕ , are both set to 35, values that lie within the range commonly used in investment-based asset pricing studies (e.g., [Zhang, 2005](#); [Belo et al., 2014](#)) and allow the model to match an annual equity premium of approximately 7%. The time discount factor is set to $\beta = 0.996$ at the quarterly frequency, corresponding to an annual risk-free rate of about 1.5%.

Panel B of Table 1 reports the production-side parameters. The capital share $\alpha = 0.33$ is consistent with standard U.S. estimates. The returns-to-scale parameter is set to $\kappa = 1.00$, implying constant returns to scale. The elasticity of demand $\eta = 4.00$ implies an average markup (absent stock-outs) of roughly 33%, in line with empirical evidence for publicly listed U.S. firms. The capital adjustment cost parameter $\xi_K = 5.10$ generates realistic cross-sectional dispersion in investment rates, while the inventory adjustment cost parameter $\xi_N = 0.10$ reflects that inventories are less costly to adjust than capital. The depreciation rates for capital and inventories are both set to 0.025 at the quarterly frequency, and the price stickiness parameter $\xi_P = 10.00$ governs nominal adjustment frictions. The fixed cost $f = 0.093$ is calibrated to match the average level of Tobin's Q in the model.

Panel C of Table 1 reports the parameters governing the exogenous shock processes. The aggregate productivity process (ρ_a, σ_a) follows [Corhay et al. \(2025\)](#) and is calibrated to

TABLE 1
Quarterly Calibration of the Benchmark Model

Description	Parameter	Value
A. Preferences		
Time discount factor	β	0.996
TFP risk price	γ_a	35.00
Demand shock risk price	γ_ϕ	35.00
B. Production		
Capital share in production	α^k	0.33
Returns to scale in production	κ	1.00
Elasticity of demand	η	4.00
Capital adjustment cost	ξ_K	5.10
Inventory adjustment cost	ξ_N	0.10
Price stickiness parameter	ξ_p	10.00
Capital depreciation rate	δ_k	0.025
Inventory depreciation rate	δ_n	0.025
Fixed operating cost	f	0.093
C. Exogenous Processes		
Persistence of TFP	ρ_a	0.974
Volatility of TFP	σ_a	0.0051
Persistence of demand	ρ_ϕ	0.974
Volatility of demand	σ_ϕ	0.0051
Persistence of idiosyncratic demand shock	ρ_s	0.931
Volatility of idiosyncratic demand shock	σ_s	0.165
Volatility of local demand shock	σ_v	0.350
Mean of local demand shock	μ_v	-0.061

This table reports the parameter values used in the benchmark quarterly calibration of the model.

match the persistence and volatility of aggregate output growth. The aggregate demand process (ρ_ϕ, σ_ϕ) is calibrated in a similar manner. Because these aggregate shocks are common to all firms, cross-sectional heterogeneity in the model is primarily driven by firm-specific demand conditions. We model product-level demand using a persistent idiosyncratic component (ρ_s, σ_s) , which generates systematic differences in inventory policies across firms. The persistence and volatility of this process are chosen to match the observed cross-sectional

dispersion in inventory-to-sales ratios in the data. Finally, the volatility of the local retail market shock, σ_v , is chosen to imply an average stock-out probability of around 10%, while the mean μ_v is set so that the expected demand shifter equals 1 in the steady state.

4.1.2 Model Fit

We solve the model using a second-order perturbation method and simulate an economy with 45 heterogeneous producers. Panel A of Table 2 reports the aggregate moments targeted in the calibration. Overall, the model provides a good fit to the key moments of firm dynamics and asset prices as targeted in the calibration.

Panel B of Table 2 examines firm characteristics sorted by their inventory-to-sales ratios, which in our model are driven by firm-specific demand shocks. Each quarter, we sort firms into three groups based on their lagged inventory-to-sales ratio and form portfolios with low (L), medium (M), and high (H) inventory-to-sales firms. We then compute the time-series averages of the portfolio characteristics and report the results in Table 2.

Firms with high inventory holdings tend to have high idiosyncratic demand realizations. This follows naturally from the persistence of demand: high current demand signals high expected future demand, inducing firms to accumulate inventories. Interestingly, the stock-out probability displays an inverse U-shaped pattern across the three portfolios. As demand rises, stock-out risk initially increases; however, for firms that already hold substantial inventories, the additional buffer more than offsets this effect, leading to lower stock-out risk among the high-inventory group.

Turning to production decisions, we find that firms facing higher demand sell more and charge higher markups, resulting in increased revenues. To meet stronger demand, these firms expand their optimal production scale by increasing the use of labor and other variable inputs. This temporary intensification of factor utilization raises the marginal cost of production, λ_{it}^X , reflecting short-run capacity pressures.

4.2 Asset Pricing Implications

We now investigate the implications of inventory holdings for firm risk and asset prices. As discussed in Section 3, inventories play a key role in shaping a firm's exposure to demand versus supply shocks, and therefore influence the risk premia embedded in equity returns.

TABLE 2
Quantitative Results

A. Aggregate Moments			
Variable	Value		
Inventory Sales Ratio	0.525		
Investment Rate	0.025		
Market-to-Book Ratio	2.129		
Markup	0.351		
Stock out probability	0.084		
$\sigma(\text{Agg sales growth})$	0.018		
$\sigma(\text{Investment growth})/\sigma(\text{Agg sales growth})$	4.121		
Excess return (%)	1.350		
$\sigma(\text{excess return})$ (%)	1.531		

B. Firm Characteristics			
Variable	L	M	H
Inventory to sales ratio	0.119	0.399	0.663
Idiosyncratic demand (φ)	0.688	1.144	1.471
Stock out probability	0.055	0.100	0.099
Sales (Y)	0.087	0.097	0.114
Price (P)	1.372	1.382	1.397
Markup (μ)	0.371	0.346	0.331
Output (X)	0.082	0.096	0.121
Labor (L)	0.026	0.037	0.049
Marginal cost (λ_X)	1.005	1.037	1.047
Market-to-book	2.308	2.150	2.011
Excess returns (%)	1.372	1.383	0.951

The model is simulated for 3000 periods using second-order perturbation methods. At each period, firms are ranked by their inventory-to-sales ratios and the reported values represent time-series averages of cross-sectional portfolio characteristics over the simulation period. The inventory-to-sales ratio is defined as the ratio of lagged inventory holdings to current-period sales. Idiosyncratic demand (φ) represents realizations of the firm-specific demand shock. Stock out probability measures the frequency of inventory depletion. Sales (Y) and output (X) represent quantities sold and produced, while price (P) is the output price. Labor (L) is the employment level, and marginal cost (λ_X) is the Lagrange multiplier on the production constraint. Markup is denoted as ν . Market-to-book ratio is the ratio of market value to lagged capital. Excess returns refer to the difference between realized return and the constant risk-free rate, reported as unlevered quarterly returns with their volatilities for both market and firm-level returns.

The last row of Table 2 reports the average risk premium for each portfolio sorted on inventory-to-sales ratios. On average, low-inventory firms command a higher risk premium than high-inventory firms, with the difference between the two portfolios approximately 1% per year. This pattern indicates that, in our model, inventory holdings serve, on average, as a hedge. To better understand how inventories shape firm risk, we next examine the impulse response functions to the two sources of aggregate risk in our model, namely, aggregate demand and aggregate supply shocks.

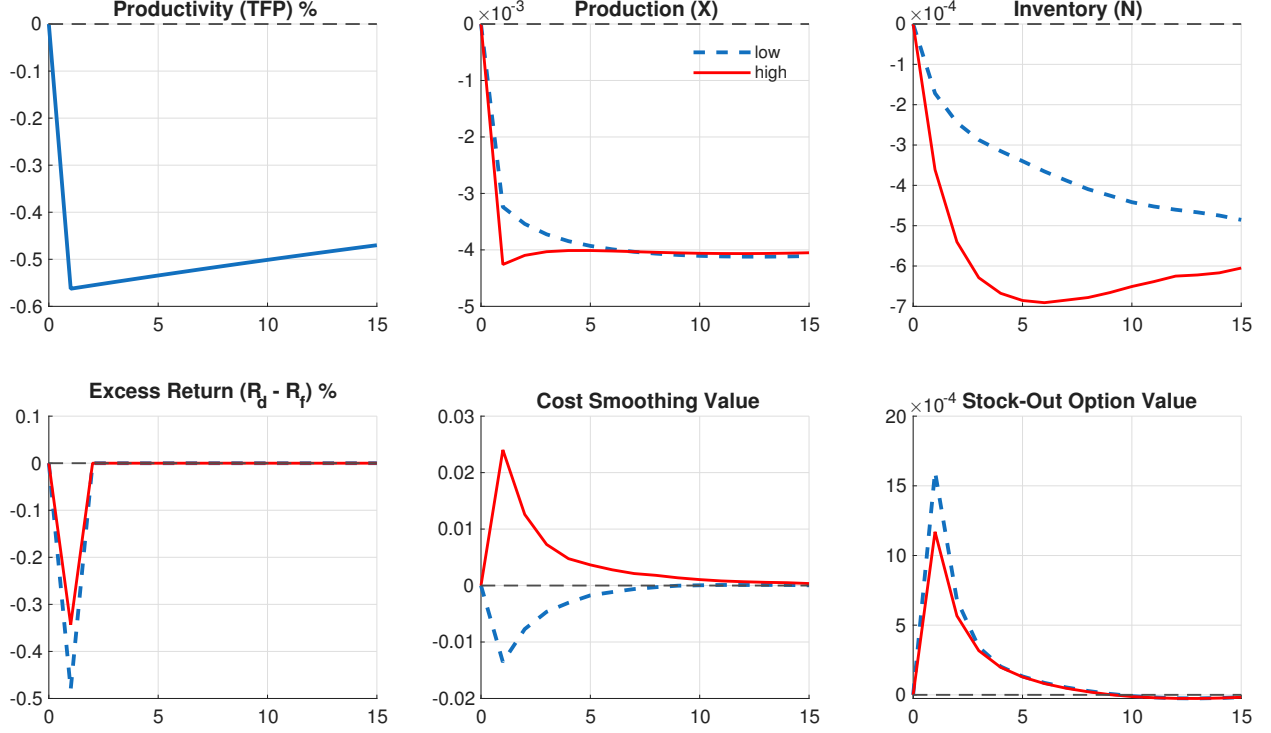
Figure 2 compares the impulse response functions of high-inventory firms (solid red) and low-inventory firms (dashed blue) following a negative aggregate productivity shock ($\varepsilon_{at} = -1$). The productivity shock increases marginal production costs and reduces output for all firms. However, high-inventory firms drop production more: they rely on previously accumulated inventories to meet demand rather than producing at a higher marginal cost, saving on costs. This is visible in the muted response of marginal cost λ_{it}^X for high-inventory firms relative to low-inventory firms. As a result, high-inventory firms experience a smaller decline in firm value on impact. Inventories act as a hedge against adverse supply conditions by smoothing marginal costs and stabilizing cash flows when productivity falls. This mechanism lowers the sensitivity of high-inventory firms' returns to supply shocks, generating a lower supply-shock beta.

The bottom-right panels illustrate the response of the two components of inventory value to the aggregate supply shock. The cost-smoothing component rises substantially for high-inventory firms, reflecting the use of inventories to substitute away from high marginal production costs. By contrast, the stock-out option value remains near zero, since a negative supply shock does not differentially affect demand or stock-out risk across firms. This pattern is consistent with the theoretical decomposition in Section 3: under supply-driven downturns, inventories primarily operate as a cost-smoothing hedge rather than as a mechanism for preserving sales in high-demand states. In short, supply shocks are absorbed through inventory drawdowns, not through changes in stock-out risk.

Figure 3 repeats the analysis for a negative aggregate demand shock ($\varepsilon_{\phi t} = -1$). The decline in demand reduces the likelihood of stock-outs, leading firms to accumulate inventories. The response of the stock-out option value, however, differs across firms. Low-inventory firms benefit from the increase in inventories because it relaxes future stock-out risk, raising the option value of holding inventories. By contrast, for high-inventory firms, additional

FIGURE 2

Impulse Responses to TFP Shock



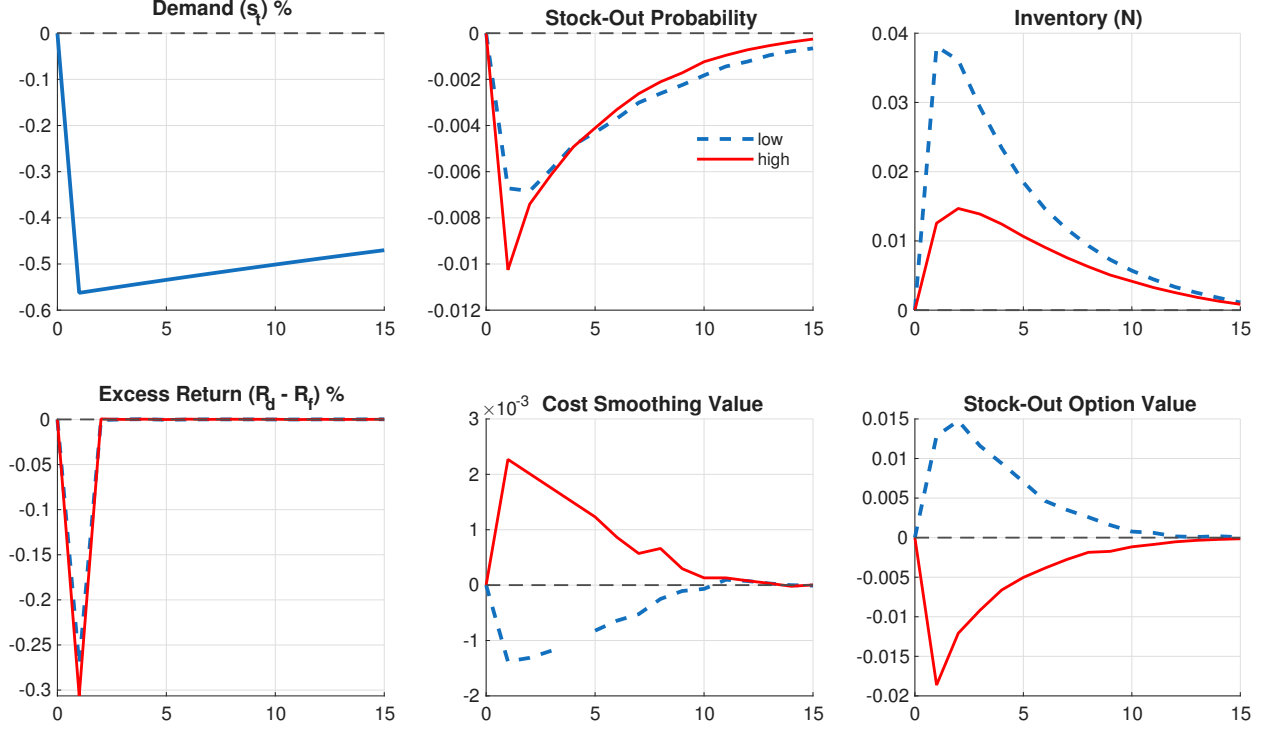
This figure presents model-implied impulse response functions following a negative productivity shock for two firms with different inventory-to-sales ratios. The “low” firms are those with low inventory-to-sales ratios (dashed), while the “high” firms are those with high inventory-to-sales ratios (solid). The figure displays the response of key variables: the dynamics of the aggregate supply shock, production X , inventory level N , excess returns, the stock-out option effect, as well as the cost-smoothing effect defined in (37).

inventory accumulation provides little marginal benefit and instead increases the burden of carrying inventories forward, reducing the stock-out option value. As shown in the bottom-right panel, the stock-out component therefore moves in opposite directions across the two types of firms.

In contrast, the cost-smoothing value of inventories remains largely unchanged in response to the demand shock, since marginal production costs are not directly affected. The dominant effect of the demand shock therefore operates through the stock-out option channel rather than through cost smoothing. As a result, high-inventory firms experience a larger decline

FIGURE 3

Impulse Responses to Aggregate Demand Shock



This figure presents model-implied impulse response functions following a negative demand shock for two firms with different inventory-to-sales ratios. The “low” firms are those with low inventory-to-sales ratios (dashed), while the “high” firms are those with high inventory-to-sales ratios (solid). The figure displays the response of key variables: the dynamics of the aggregate demand shock, stock-out probability $1 - F(v^*)$, inventory level N , excess returns, the stock-out option effect, as well as the cost-smoothing effect shown in (37).

in firm value and a stronger return response on impact. In equilibrium, inventories amplify firms’ exposure to demand shocks, increasing the demand-shock beta of high-inventory firms.

These results have direct asset pricing implications. Using the firm’s Euler equation, the expected return on equity for firm i can be written as:

$$\mathbb{E}[R_{it+1}^e] = \beta_{it}^a \cdot \gamma_a + \beta_{it}^\phi \cdot \gamma_\phi, \quad (43)$$

where β_{it}^a and β_{it}^s denote the firm’s exposure (beta) to aggregate productivity (supply) shocks

and aggregate demand shocks, respectively, and γ_a and γ_s are the corresponding prices of risk.

The cross-sectional return difference between low-inventory and high-inventory firms therefore reflects two opposing forces:

$$\mathbb{E}[R_{Lt+1}^e] - \mathbb{E}[R_{Ht+1}^e] = \underbrace{(\beta_{Lt}^a - \beta_{Ht}^a)}_{\text{Cost-smoothing} > 0} \cdot \underbrace{\gamma_a}_{> 0} + \underbrace{(\beta_{Lt}^\phi - \beta_{Ht}^\phi)}_{\text{Stock-out} < 0} \cdot \underbrace{\gamma_\phi}_{> 0}. \quad (44)$$

High-inventory firms are better able to draw down inventories in response to adverse productivity shocks, which reduces their exposure to supply-driven fluctuations in marginal costs. This generates a *hedging benefit* reflected in a lower supply beta, $\beta_{Ht}^a < \beta_{Lt}^a$, and therefore increases the Low minus High spread. In contrast, high-inventory firms benefit more from positive demand states because they are more likely to avoid stock-outs and sell at higher markups. As a result, they load more heavily on demand shocks, $\beta_{Ht}^s > \beta_{Lt}^s$, which reduces the Low minus High spread.

To assess the net effect, we shut down each aggregate shock individually and recompute the return spread. We find that the supply-shock channel contributes +1.66% per year to the Low-minus-High inventory return spread, whereas the demand-shock channel contributes −0.53% per year. Thus, the positive return premium associated with low-inventory firms primarily reflects their greater exposure to supply-driven variation in marginal costs, while the demand-driven stock-out option partially offsets this effect.

We assess the robustness of our findings in two key dimensions (see Appendix for details). First, we replace the demand-based source of firm heterogeneity with firm-specific productivity shocks. The model produces nearly identical patterns: firms with larger inventory positions continue to load more on demand shocks and less on supply shocks. This demonstrates that our results are not driven by the particular choice of heterogeneity and that inventories remain the central mechanism linking firm characteristics to risk exposures. Second, we consider a version of the model with no inventories. In this case, the return spread between firms with high versus low idiosyncratic demand realizations becomes negligible. This confirms that the inventory channel—rather than differences in underlying demand conditions alone—is essential for generating the cross-sectional variation in expected stock returns.

Taken together, the findings show that inventories are not merely passive buffers of production, but key determinants of firm-level risk. They hedge firms against adverse supply-side fluctuations by smoothing marginal costs, yet increase exposure to demand-driven shocks. This dual role shapes both the return response to business cycle shocks and the expected compensation investors require in equilibrium.

5 Empirical results

In this section, we take the model to the data and examine its key empirical predictions. In particular, we investigate how inventory holdings relate to firm risk exposures and expected returns.

5.1 Sample construction

We obtain equity return data from the Center for Research in Security Prices (CRSP) and merge it with annual accounting data from Compustat. Firms must have valid observations in both databases to be included in the sample. Following [Fama and French \(1992\)](#), we restrict attention to ordinary common shares listed on the NYSE, AMEX, or Nasdaq (CRSP share codes 10 and 11), thereby excluding American depositary receipts, real estate investment trusts, and units of beneficial interest. We further exclude financial firms (SIC codes 6000–6999) and regulated utilities (SIC codes 4900–4999), whose balance sheet structures and operating environments differ substantially from those of non-financial firms.

Following [Belo and Lin \(2012\)](#), we construct the inventory-to-sales ratio as the ratio of inventory (Compustat item INVT) to sales (SALE). We exclude firms that report zero inventory in more than half of their firm-year observations, as such firms are unlikely to engage in inventory management in a meaningful way. We collect additional firm characteristics for our empirical analysis. The book-to-market ratio (BM) is constructed following [Fama and French \(1992\)](#), using Compustat book equity divided by market equity. Market capitalization (SIZE) is measured in June of year t as the product of share price and shares outstanding. The asset growth measures the annual percentage growth of total asset (AT) and book leverage is the ratio of total debt (DT) to total asset (AT). To measure gross profitability, we subtract cost of goods sold (COGS) from sales (SALE) and divide by the total asset (AT).

TABLE 3
Quintile Portfolio Characteristics

	$\frac{\text{INVT}}{\text{SALE}}$	BM	Size	Book Leverage	Asset Growth	Gross Profitability	Markup	Nobs
L	0.05	0.79	1704.0	0.22	0.12	0.41	1.56	33899
2	0.1	0.78	2737.0	0.22	0.11	0.44	1.56	24325
3	0.14	0.82	2493.0	0.22	0.1	0.43	1.46	23147
4	0.18	0.86	1817.0	0.22	0.11	0.41	1.42	24855
H	0.33	0.94	983.0	0.23	0.12	0.34	1.41	36785

This table reports summary statistics for firms sorted into quintiles based on their inventory-to-sales ratio (INVT/SALE). We report the average book-to-market ratio (BM), market capitalization (Size), book leverage, asset growth, gross profitability, and markup for each quintile. Firms are sorted into five groups each year, where L denotes the lowest 20% of firms and H denotes the highest 20%.

Finally, we measure firm-level markups using the production-based approach of [Hall \(1988\)](#), as implemented by [De Loecker et al. \(2020\)](#). This method exploits the firm’s optimal markup condition linking marginal cost to the elasticity of output with respect to a variable input. We use cost of goods sold (COGS) as our measure of variable input expenditures, which captures materials, energy, and labor expenses. The corresponding variable input elasticity is estimated from a standard production function, allowing us to compute markups as the ratio of revenue to variable cost shares.

Table 3 reports summary statistics for five portfolios formed on the inventory-to-sales ratio. In line with the model, firms with higher inventory positions tend to have higher book-to-market ratios, lower markups, and lower gross profitability. High-inventory firms are also smaller on average. Interestingly, we observe no meaningful differences across portfolios in asset growth or leverage, suggesting that the inventory-return relationship, if any, is not driven by variation in investment activity or financial risk.

5.2 Inventory and Stock Returns: Unconditional Tests

In this section, we examine the implications of inventory holdings for firms’ unconditional risk and expected returns.

Time Series. We begin with a time-series portfolio analysis. Each June of year t , we sort firms into five portfolios based on the quintile distribution of their lagged inventory-to-sales ratios, performing the sort *within* industries⁴ to account for industry fixed effects. We then compute value- and equal-weighted excess returns from July of year t through June of year $t + 1$, rebalancing the portfolios annually. Examining the performance of these portfolios over the sample period allows us to assess whether inventory holdings serve, on average, as a hedge against aggregate fluctuations or instead increase firms’ exposure to systematic risk.

Table 4 reports mean excess returns for the quintile portfolios, ranging from the lowest inventory-to-sales quintile (L) to the highest (H). The final row (LMH) reports the return on a zero-cost portfolio that is long firms in the lowest inventory quintile and short firms in the highest. Newey–West standard errors are used to compute the associated t -statistics. The first columns of the table present raw excess returns.

The results reveal a strong, monotonic decline in average returns as inventory-to-sales ratios increase. The value-weighted LMH portfolio (Panel A) earns an annualized excess return of 2.3% (t -stat = 1.65), while the equal-weighted LMH portfolio (Panel B) earns 3.65% (t -stat = 4.58). These magnitudes are economically meaningful and consistent with the model’s prediction that firms with larger inventory positions earn lower expected returns. This pattern suggests that, over our sample period, the cost-smoothing (supply-hedging) channel of inventories dominates their exposure to demand-driven fluctuations, implying that supply shocks are quantitatively more important in driving inventory-related return differences.

The remaining columns of Table 4 report alphas from standard asset pricing models, including the CAPM, the Fama–French three-factor model, the Fama–French five-factor model (Fama and French, 2015), and the q -factor model of Hou et al. (2015). The inventory return spread remains large and statistically significant after controlling for these factors, for both value- and equal-weighted specifications. This indicates that inventory holdings capture a distinct dimension of systematic risk not spanned by standard factor portfolios.

Figure 4 plots the time-series performance of the inventory-sorted portfolios. Panel A shows the cumulative abnormal returns of the Low- and High-inventory portfolios, com-

⁴Industries are defined using the Fama–French 12-industry classification, which offers a balance between sector granularity and sufficient firm counts within each group. All results are robust to alternative industry definitions as well as to unconditional sorts.

TABLE 4
Time-Series Tests

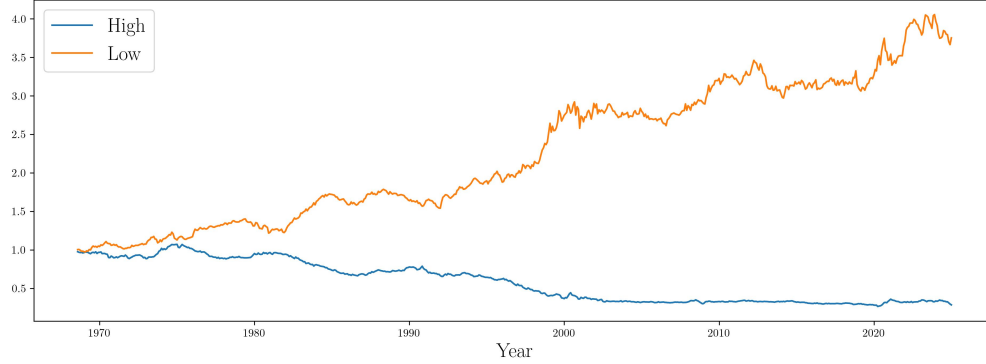
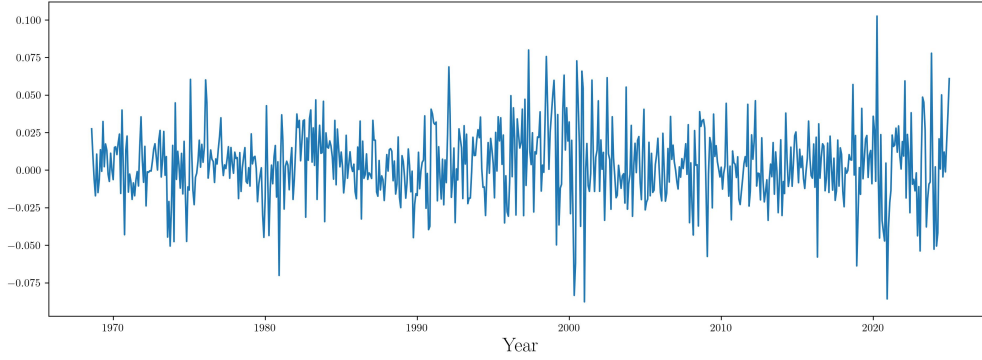
A. Value-Weighed					
	$r_{it} - r_f$	α_{CAPM}	α_{FF3}	α_{FF5}	α_{Q4}
L	8.32	1.06	2.11	2.5	7.74
2	7.38	1.3	1.35	0.13	3.89
3	7.74	0.94	0.92	-0.23	3.98
4	6.37	-1.01	-1.31	-2.24	2.69
H	6.02	-1.8	-1.94	-2.04	4.14
LMH	2.3* (1.65)	2.86** (2.08)	4.05*** (3.29)	4.54*** (3.7)	3.6*** (2.65)

B. Equally-Weighed					
	$r_{it} - r_f$	α_{CAPM}	α_{FF3}	α_{FF5}	c
L	11.01	2.85	2.69	3.24	9.41
2	10.78	2.72	2.09	1.95	8.25
3	10.14	1.98	1.05	0.55	7.06
4	10.11	1.76	1.0	0.96	7.77
H	7.36	-1.16	-1.6	-0.85	6.18
LMH	3.65*** (4.58)	4.01*** (5.35)	4.29*** (6.38)	4.09*** (5.65)	3.23*** (4.49)

This table reports excess returns ($r_{it} - r_{ft}$) and risk-adjusted returns from CAPM (α_{CAPM}), Fama–French three-factor (α_{FF3}), Fama–French five-factor (α_{FF5}), and q-factor four-factor (α_{q4}) models for quintile portfolios and the High–minus–Low (H–L) spread. t -statistics are in parentheses and use Newey–West standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

puted relative to the Fama–French five-factor model and Panel B plots the monthly abnormal returns of the LMH portfolio. The Low-inventory portfolio steadily outperforms the High-inventory portfolio over the sample period, consistent with our baseline result that, on average, inventory holdings act as a hedge against aggregate supply fluctuations. At higher frequency, the performance of the LMH spread varies substantially over time, suggesting that

FIGURE 4

Time Series Performance Inventories-sorted Portfolio**A. Cumulative abnormal returns****B. Abnormal returns LMH**

This figure shows the time-series performance of the Low-minus-High (LMH) inventory-to-sales portfolio. Panel A plots the cumulative abnormal returns for the High (blue) and Low (orange) inventory-to-sales portfolios. Panel B displays the monthly abnormal returns of the LMH portfolio, constructed by going long the Low portfolio and short the High portfolio. Abnormal returns are computed relative to the Fama–French five-factor model.

the inventory premium is state-dependent. This motivates (along with our model results) our conditional analysis below, where we examine whether the differential exposure of Low- and High-inventory firms to supply versus demand shocks explains the time variation in returns.

Cross-Section. Next, we verify the relationship between inventory-to-sales ratios and stock returns in the cross-section using panel regressions. Specifically, we estimate monthly

predictive regressions of the form:

$$R_{it+1} - R_{ft+1} = \beta_1 \log\left(\frac{\text{INVT}_{it}}{\text{SALE}_{it}}\right) + X'_{it}\beta + \alpha_k + \alpha_t + \varepsilon_{it+1}, \quad (45)$$

where $R_{it+1} - R_{ft+1}$ is the excess return of firm i in month $t + 1$, $\log(\text{INVT}_{it}/\text{SALE}_{it})$ is the lagged inventory-to-sales ratio, and X_{it} is a vector of standard firm-level controls known to explain the cross-section of expected returns. These controls include log firm size, book-to-market, momentum, short-term reversal, cash-to-assets, return on assets, asset growth, gross profitability, share issuance growth, and accruals. We also explicitly include inventory growth to ensure that the inventory-to-sales ratio captures information distinct from working-capital or accrual-based investment effects. Industry fixed effects (α_k) and time fixed effects (α_t) are included to absorb sectoral heterogeneity and common shocks.

Table 5 reports the coefficient estimates and associated t -statistics, with standard errors double-clustered by firm and month. We find a strong negative association between inventory-to-sales ratios and subsequent stock returns. Quantitatively, a one-standard-deviation increase in log inventory-to-sales (8.20%) predicts a 0.22% decline in next-month returns (column 1). Consistent with [Belo and Lin \(2012\)](#), column (2) shows that firms with high inventory growth earn significantly lower returns, a pattern they interpret through a q -theory mechanism in which low cost of capital induces firms to accumulate inventories. However, when we include both the inventory *level* and inventory *growth* measures in the regression (column 3), both coefficients remain economically large and statistically significant. This indicates that the level of inventories captures a distinct channel—linked to differences in exposure to supply and demand shocks—rather than simply reflecting variation in marginal q or investment frictions. Finally, the coefficient on inventory-to-sales remains robustly negative and statistically significant after controlling for the full set of standard firm characteristics and including industry fixed effects (columns 4–6). Taken together, these results reinforce the portfolio evidence: inventory levels contain incremental information about firms’ systematic risk exposures that is not subsumed by inventory growth or by conventional return predictors.

TABLE 5
Cross-Sectional Asset Pricing Tests

	(1)	(2)	(3)	(4)	(5)	(6)
$\log\left(\frac{\text{INVT}_{it-1}}{\text{SALE}_{it-1}}\right)$	-2.35*** (-8.82)		-2.02*** (-7.72)	-1.39*** (-5.25)		-1.39*** (-5.28)
$d \log \text{INVT}_{it-1}$		-0.64*** (-7.39)	-0.56*** (-6.52)		-0.05 (-0.65)	-0.02 (-0.25)
$\log \text{SIZE}_{it-1}$	-0.11*** (-2.60)	-0.10** (-2.35)	-0.11*** (-2.60)	-0.10*** (-2.91)	-0.10*** (-2.81)	-0.10*** (-2.91)
$\log \text{BM}_{it-1}$	0.54*** (8.02)	0.47*** (7.14)	0.50*** (7.45)	0.46*** (7.05)	0.45*** (6.88)	0.46*** (7.01)
$R_{it-2,t-12}$	1.04*** (5.45)	1.00*** (5.26)	1.00*** (5.26)	0.88*** (4.56)	0.88*** (4.54)	0.88*** (4.56)
R_{it-1}	-6.09*** (-8.83)	-6.09*** (-8.84)	-6.10*** (-8.85)	-6.10*** (-8.79)	-6.10*** (-8.79)	-6.10*** (-8.79)
Nobs	1576819	1576819	1576819	1426459	1426459	1426459
R^2	0.1310	0.1310	0.1311	0.1309	0.1309	0.1309
Additional controls	N	N	N	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y

This table estimates the relation between future excess stock returns and firms' inventory-to-sales ratios using the panel regression specified in Equation (45). Coefficient estimates are reported along with t -statistics (in parentheses), where standard errors are double-clustered by firm and month. The specification controls for standard firm characteristics, including cash-to-assets, ROA, asset growth, gross profitability, share issuance growth, and accruals. To address zero-inventory observations, we compute $\log(1 + \frac{\text{INVT}}{\text{SALE}})$. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5.3 Inventory and Stock Returns: Conditional Tests

In this section, we test a key prediction of our model: inventory holdings differentially affect firms' exposures to aggregate demand and supply shocks. Specifically, the model implies that inventories reduce firms' sensitivity to supply-driven fluctuations (through the cost-smoothing channel), while increasing their sensitivity to demand-driven fluctuations (through

the stock-out option channel). These differential beta exposures, in turn, shape the return spread between low- and high-inventory firms documented in the unconditional tests above.

5.3.1 Identification of Demand and Supply Shocks.

In order to test our prediction, we first need to identify aggregate demand and supply shocks.

We follow [Bekaert et al. \(2025\)](#) to extract aggregate supply and demand shocks using revisions in professional forecasts. Specifically, we use quarter-to-quarter forecast errors in real GDP growth and inflation from the Survey of Professional Forecasters and classify them into structural shocks based on a sign restriction: shocks that move output and inflation in the same direction are labeled *demand* shocks, whereas shocks that move them in opposite directions are labeled *supply* shocks. This procedure yields time series of aggregate demand and supply shocks that are orthogonal and economically interpretable.

Figure 5 plots the time series of the estimated aggregate demand and supply shocks. Both series exhibit similar unconditional volatilities of approximately 1.1%, but their dynamics differ markedly over time. Supply shocks display greater variability in the earlier part of the sample, whereas demand shocks dominate more recent fluctuations. The correlation between the two series is weak (0.015), confirming that the identification procedure successfully isolates two economically distinct sources of aggregate fluctuations, consistent with the model.

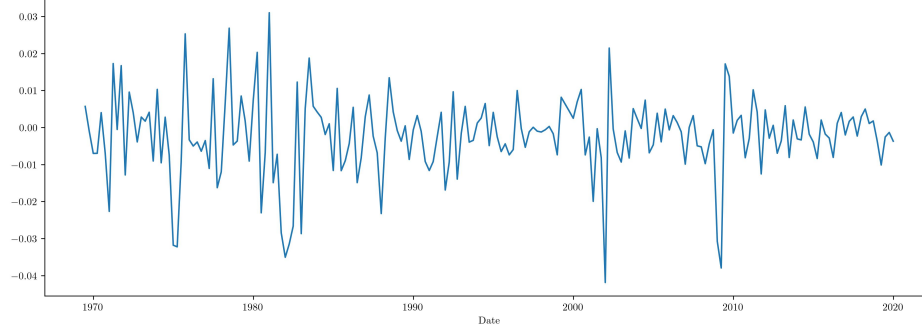
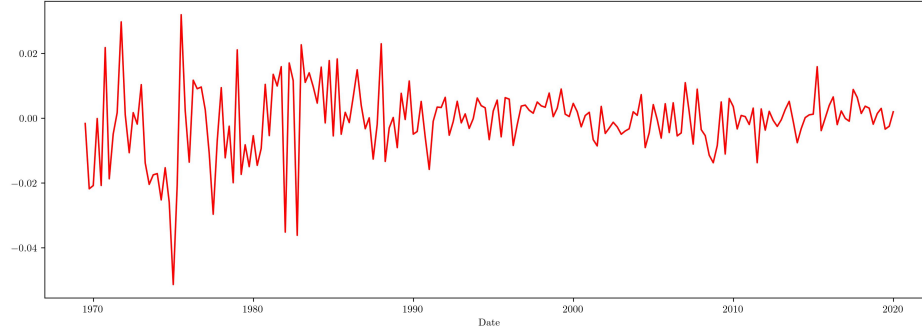
5.3.2 Inventories, demand, and supply shocks.

Our model predicts that firms with high inventory positions should be relatively hedged against supply shocks, but more exposed to demand shocks. To test this prediction, we relate the Low-minus-High (LMH) inventory portfolio returns to the estimated aggregate shocks using the following regression:

$$R_{Lt}^e - R_{Ht}^e = \beta^{\text{Supply}} \cdot \hat{\varepsilon}_t^{\text{Supply}} + \beta^{\text{Demand}} \cdot \hat{\varepsilon}_t^{\text{Demand}} + \beta' \cdot X_t + \varepsilon_t, \quad (46)$$

where $\hat{\varepsilon}_t^{\text{Supply}}$ and $\hat{\varepsilon}_t^{\text{Demand}}$ are the estimated aggregate supply and demand shocks, and $R_{Lt}^e - R_{Ht}^e$ is the LMH return spread constructed in Section 5.2, and X_t is a vector of return factors. The model predicts $\beta^{\text{Supply}} > 0$ and $\beta^{\text{Demand}} < 0$.

FIGURE 5

Aggregate Demand and Supply Shocks**A. Aggregate Demand Shocks****B. Aggregate Supply Shocks**

This figure plots the estimated aggregate demand (Panel A) and supply shocks (Panel B), extracted following the identification procedure in [Bekaert et al. \(2025\)](#). Demand shocks are identified as innovations that move output and inflation in the same direction, while supply shocks move them in opposite directions.

Table 6 reports the results. The coefficient estimates provide clear support for the model's prediction. Low-inventory firms are significantly less exposed to demand shocks, but more exposed to supply shocks, relative to high-inventory firms. This pattern holds both when the shocks are included separately (columns (1)–(2)) and jointly (column (3)). The magnitudes are economically meaningful and statistically significant.

Columns (4)–(6) repeat the analysis while controlling for the Fama–French three factors. The coefficients remain virtually unchanged, confirming that the differential shock exposures are not absorbed by standard return factors. Overall, the results provide strong empirical

TABLE 6
LMH Exposure to Demand and Supply Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\epsilon}_t^{\text{Demand}}$	-0.454* (-1.87)		-0.462** (-2.09)	-0.444* (-1.89)		-0.447** (-2.13)
$\hat{\epsilon}_t^{\text{Supply}}$		0.470** (2.00)	0.477** (2.04)		0.410* (1.85)	0.414* (1.92)
LMH Factors Control	N	N	N	Y	Y	Y
Nobs	203	203	203	203	203	203
R-squared	0.0125	0.0135	0.0264	0.1685	0.1668	0.1788

This table examines the relation between inventory holdings and firms' exposure to aggregate demand and supply shocks. We regress the quarterly return of the Low-minus-High (LMH) inventory-to-sales portfolio on the identified demand and supply shocks. Factor controls adjust the LMH for the Fama–French five-factor model. Newey–West adjusted t -statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

support for the key prediction of the model: inventory holdings shape firms' exposure to different sources of aggregate risk, lowering exposure to supply-driven fluctuations while increasing exposure to demand-driven fluctuations.

5.3.3 Supply and Demand Risk and the Inventory Premium.

We now examine whether time variation in aggregate demand and supply risk prices helps explain fluctuations in the inventory premium. Equation (44) implies that the premium on the Low-minus-High inventory-to-sales portfolio should covary with changes in the risk compensation for aggregate supply and demand shocks. Periods in which the price of aggregate supply risk is high should correspond to a larger LMH premium, since low-inventory firms are more exposed to supply shocks. Conversely, when the price of aggregate demand risk rises, the LMH premium should decline, as high-inventory firms are disproportionately exposed to demand-driven fluctuations.

To test this prediction, we need a proxy for the time-varying prices of aggregate supply

and demand risk. We estimate these prices using a standard two-pass [Fama and MacBeth \(1973\)](#) procedure, following the approach of [Cochrane \(2005\)](#) and [Bansal et al. \(2005\)](#). In each month t , we run the following cross-sectional regression across 100 size–book-to-market sorted portfolios⁵:

$$R_{it} = \hat{\gamma}_t^0 + \beta_{i,t-1}^{\text{demand}} \cdot \hat{\gamma}_t^{\text{demand}} + \beta_{i,t-1}^{\text{supply}} \cdot \hat{\gamma}_t^{\text{supply}} + \beta_{i,t-1}^{\text{FF5}} \cdot \hat{\gamma}_t^{\text{FF5}} + \varepsilon_{it}, \quad (47)$$

where $\beta_{i,t-1}^{\text{demand}}$ and $\beta_{i,t-1}^{\text{supply}}$ are estimated by regressing portfolio returns on the estimated aggregate demand and supply shocks, and $\beta_{i,t-1}^{\text{FF5}}$ are obtained from the Fama–French five-factor model. All betas are estimated over a rolling 3-year window. The resulting coefficients $\hat{\gamma}_t^{\text{demand}}$ and $\hat{\gamma}_t^{\text{supply}}$ provide a time series of the prices of demand and supply risk, which we then relate to movements in the LMH inventory premium.

Next, we formally test the empirical analogue of Equation (44):

$$R_{Lt}^e - R_{Ht}^e = b^{\text{supply}} \cdot \hat{\gamma}_t^{\text{supply}} + b^{\text{demand}} \cdot \hat{\gamma}_t^{\text{demand}}, \quad (48)$$

where $\hat{\gamma}_t^{\text{supply}}$ and $\hat{\gamma}_t^{\text{demand}}$ are the estimated prices of supply and demand risk from the previous regression. To mitigate noise arising from the two-pass beta and price-of-risk estimates, we smooth both sides of the regression using a one-year moving average.⁶ The model predicts $b^{\text{supply}} > 0$ and $b^{\text{demand}} < 0$.

Table 7 reports the results. Column (1) strongly supports the model’s prediction: when the price of supply risk rises, the LMH premium increases, whereas periods with a higher price of demand risk are associated with a lower LMH premium. Column (2) shows that these results are essentially unchanged when the dependent variable is the LMH portfolio’s abnormal return after controlling for the Fama–French five factors.

To further address potential estimation error in $\hat{\gamma}_t^{\text{supply}}$ and $\hat{\gamma}_t^{\text{demand}}$, we repeat the analysis using indicator variables equal to one when the annual average price of risk exceeds its 80th percentile, and zero otherwise. The results remain robust: aggregate supply and demand risk exert opposite effects on the inventory premium, consistent with the model’s prediction that inventory holdings create distinct exposure to fundamental business-cycle shocks.

⁵We obtain the 100 size–book-to-market sorted portfolios from the Kenneth French Data Library and aggregate the monthly returns to the quarterly frequency.

⁶Results are robust to alternative smoothing windows.

TABLE 7

LMH Premium and the Prices of Demand and Supply Risk

	(1)	(2)	(3)	(4)
$\hat{\gamma}^{\text{demand}}$	-1.277** (-2.33)	-1.436** (-2.44)		
$\hat{\gamma}^{\text{supply}}$	1.138*** (2.83)	1.324*** (3.23)		
$\mathbb{I}\{\hat{\gamma}_t^{\text{demand}} > \hat{\gamma}_{80}^{\text{demand}}\}$			-0.011* (-1.94)	-0.007* (-1.66)
$\mathbb{I}\{\hat{\gamma}_t^{\text{supply}} > \hat{\gamma}_{80}^{\text{supply}}\}$			0.020** (4.30)	0.021** (3.99)
LMH Factors Control	N	Y	N	Y
Nobs	188	188	188	188
R-squared	0.0789	0.1326	0.1299	0.1572

This table investigates how the inventory premium covaries with the prices of aggregate demand and supply risk. We regress the return on the Low-minus-High (LMH) inventory-to-sales portfolio on the estimated demand and supply prices of risk from Equation (47). “LMH Factor Controls” denotes the LMH abnormal return after adjusting for the Fama–French five-factor model. To reduce estimation noise, all variables are averaged at the annual frequency prior to estimation. The indicators $\mathbb{I}\{\hat{\gamma}_t^{\text{supply}} > \hat{\gamma}_{80}^{\text{supply}}\}$ and $\mathbb{I}\{\hat{\gamma}_t^{\text{demand}} > \hat{\gamma}_{80}^{\text{demand}}\}$ equal one when the corresponding price of risk exceeds its 80th percentile and zero otherwise. Newey–West adjusted t -statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

6 Conclusion

This paper develops a production-based asset pricing framework with inventory management. The model shows that the shadow value of inventories decomposes into two opposing components: a cost-smoothing value that hedges adverse supply shocks by allowing firms to draw down inventories when marginal costs spike, and a stock-out option value that amplifies exposure to demand shocks by increasing (reducing) revenues in high- (low-) demand states. This duality implies that inventories can serve either as a hedge or as a source of systematic risk, depending on whether supply or demand forces dominate macroeconomic fluctuations.

As a result, inventory holdings become a key state variable governing the sign and magnitude of firms' betas with respect to fundamental shocks.

Empirically, we find strong support for the model's predictions. We measure the hedging effect of inventories by constructing a portfolio that is long low inventory-to-sales firms and short high inventory-to-sales firms—controlling for industry effects—referred to as the LMH portfolio. Unconditionally, the LMH premium is positive, indicating that high inventory-to-sales firms earn significantly lower average returns. This pattern suggests that supply shocks are, on average, quantitatively more important for firms' risk exposures. Second, using professional forecast revisions to construct aggregate supply and demand shocks, we show that the LMH portfolio loads negatively on demand shocks but positively on supply shocks, exactly as the model predicts. Third, the inventory premium, as measured by the LMH portfolio, varies systematically with the prices of these risks: it is larger when supply risk is more highly compensated and smaller when demand risk commands a higher premium. These results are robust across portfolio sorts and factor adjustments, and they closely match model-simulated moments.

Taken together, our findings highlight inventories as a central mechanism through which firms absorb and transmit macroeconomic disturbances into asset prices. Inventory management is not merely an operational decision but a key determinant of firms' cyclical risk exposures and expected returns. More broadly, our results suggest that the Low-minus-High inventory portfolio offers a useful window into the underlying sources of macroeconomic shocks and uncertainty. Periods in which the LMH portfolio pays high return are more likely driven by supply-side forces, whereas periods of LMH underperformance tend to reflect stronger demand-driven risk. Moreover, if a recession coincides with a decline in the LMH portfolio, the evidence points toward a demand-driven contraction; if LMH rises, supply forces are the more plausible driver. In this sense, inventory-sorted returns provide a novel, market-based indicator for distinguishing between demand- and supply-driven business cycle variation.

References

- Aguerrevere, F. L. (2009). Real options, product market competition, and asset returns. *The Journal of Finance* 64(2), 957–983.
- Ai, H., J. E. Li, and J. Tong (2025). Equilibrium value and profitability premiums. *Available at SSRN 5267354*.
- Bachmann, R. and C. Bayer (2013, September). "wait-and-see" business cycles? *Journal of Monetary Economics* 60(6), 704–719.
- Bansal, R., R. F. Dittmar, and C. T. Lundblad (2005). Consumption, dividends, and the cross section of equity returns. *The Journal of Finance* 60(4), 1639–1672.
- Bekaert, G., E. Engstrom, and A. Ermolov (2025). Uncertainty and the economy: The evolving distributions of aggregate supply and demand shocks. *American Economic Journal: Macroeconomics*.
- Belo, F. and X. Lin (2012). The inventory growth spread. *The Review of Financial Studies* 25(1), 278–313.
- Belo, F., X. Lin, and M. A. Vitorino (2014). Brand capital and firm value. *Review of Economic Dynamics* 17(1), 150–169.
- Belo, F., X. Lin, and F. Yang (2019). External equity financing shocks, financial flows, and asset prices. *The Review of Financial Studies* 32(9), 3500–3543.
- Belo, F. and J. Yu (2013). Government investment and the stock market. *Journal of Monetary Economics* 60(3), 325–339.
- Bils, M. and J. A. Kahn (2000, June). What inventory behavior tells us about business cycles. *American Economic Review* 90(3), 458–481.
- Blinder, A. S. (1981). Inventories and sticky prices: More on the microfoundations of macroeconomics.
- Blinder, A. S. and L. J. Maccini (1991, Winter). Taking stock: A critical assessment of recent research on inventories. *Journal of Economic Perspectives* 5(1), 73–96.

- Bretscher, L., A. Hsu, and A. Tamoni (2020a). Fiscal policy driven bond risk premia. *Journal of Financial Economics* 138(1), 53–73.
- Bretscher, L., A. Hsu, and A. Tamoni (2020b). The real response to uncertainty shocks: The risk premium channel. *Georgia Tech Scheller College of Business Research Paper* (17-13).
- Bustamante, M. C. and A. Donangelo (2017). Product market competition and industry returns. *The Review of Financial Studies* 30(12), 4216–4266.
- Chen, H., W. Dou, H. Guo, and Y. Ji (2020). Feedback and contagion through distressed competition. *The Rodney L. White Center Working Papers Series at the Wharton School, Jacobs Levy Equity Management Center for Quantitative Financial Research Paper*.
- Clara, N., A. Corhay, and H. Kung (2021). Firm product concentration and asset prices. *Available at SSRN 3488428*.
- Cochrane, J. H. (2005). *Asset pricing: Revised edition*. Princeton university press.
- Corhay, A. (2017). Industry competition, credit spreads, and levered equity returns. *Rotman School of Management working paper* (2981793).
- Corhay, A., H. Kung, and L. Schmid (2020). Competition, Markups, and Predictable Returns. *Review of Financial Studies* 33(12).
- Corhay, A., J. Li, and J. Tong (2025). Price markup shocks and asset prices. *Rotman School of Management Working Paper*.
- Croce, M. M. (2014). Long-run productivity risk: A new hope for production-based asset pricing? *Journal of Monetary Economics* 66, 13–31.
- Croce, M. M., T. T. Nguyen, S. Raymond, and L. Schmid (2019). Government debt and the returns to innovation. *Journal of Financial Economics* 132(3), 205–225.
- Crouzet, N. and H. Oh (2016). What do inventories tell us about news-driven business cycles? *Journal of Monetary Economics* 79, 49–66.
- De Loecker, J., J. Eeckhout, and G. Unger (2020). The Rise of Market Power and the Macroeconomic Implications. *The Quarterly Journal of Economics* 135(May), 561–644.

- Donangelo, A., F. Gourio, M. Kehrig, and M. Palacios (2019). The cross-section of labor leverage and equity returns. *Journal of Financial Economics* 132(2), 497–518.
- Doshi, H. and P. Kumar (2021). Capital investment and asset returns in dynamic oligopolies.
- Dou, W. W., Y. Ji, and W. Wu (2021). Competition, profitability, and discount rates. *Journal of Financial Economics* 140(2), 582–620.
- Eichenbaum, M. (1989, September). Some empirical evidence on the production level and production cost smoothing models of inventory investment. *American Economic Review* 79(4), 853–864.
- Eisfeldt, A. L. and D. Papanikolaou (2013). Organization capital and the cross-section of expected returns. *Journal of Finance* 68(4), 1365–1406.
- Fama, E. F. and K. R. French (1992). The cross-section of expected stock returns. *the Journal of Finance* 47(2), 427–465.
- Fama, E. F. and K. R. French (2015). A five-factor asset pricing model. *Journal of financial economics* 116(1), 1–22.
- Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81(3), 607–636.
- Favilukis, J. and X. Lin (2013). Long run productivity risk and aggregate investment. *Journal of Monetary Economics* 60(6), 737–751.
- Grigoris, F., Y. Hu, and G. Segal (2022, 07). Counterparty risk: Implications for network linkages and asset prices. *The Review of Financial Studies* 36(2), 814–858.
- Grigoris, F. and G. Segal (2021). Investment under up-and downstream uncertainty. *Unpublished working paper. Indiana University*.
- Grigoris, F. and G. Segal (2024). The utilization premium. *Management Science* 70(1), 207–224.
- Hall, R. E. (1988). The relation between price and marginal cost in us industry. *Journal of political Economy* 96(5), 921–947.

- Herskovic, B., T. Kind, and H. Kung (2018). Micro uncertainty and asset prices. *Available at SSRN 3220825*.
- Hou, K., C. Xue, and L. Zhang (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies* 28(3), 650–705.
- Jones, C. S. and S. Tuzel (2013, March). Inventory investment and the cost of capital. *Journal of Financial Economics* 107(3), 557–579.
- Kahn, J. A. (1987). Inventories and the volatility of production. *The American Economic Review*, 667–679.
- Khan, A. and J. K. Thomas (2007, July). Inventories and the business cycle: An equilibrium analysis of (s,s) policies. *Econometrica* 75(4), 1165–1201.
- Knesl, J. (2018). Automation and the displacement of labor by capital: Asset pricing theory and empirical evidence. *Available at SSRN 3293405*.
- Kogan, L. and D. Papanikolaou (2014). Growth opportunities, technology shocks, and asset prices. *The journal of finance* 69(2), 675–718.
- Kryvtsov, O. and V. Midrigan (2012, 07). Inventories, markups, and real rigidities in menu cost models. *The Review of Economic Studies* 80(1), 249–276.
- Kuehn, L.-A. and L. Schmid (2014). Investment-Based Corporate Bond Pricing. *The Journal of Finance*.
- Kuehn, L.-a., M. Simutin, and J. J. Wang (2017). A labor capital asset pricing model. *The Journal of Finance* 72(5), 2131–2178.
- Kung, H. and L. Schmid (2015). Innovation, growth, and asset prices. *Journal of Finance* 70(3), 1001–1037.
- Ramey, V. A. and K. D. West (1999). Inventories. *Handbook of macroeconomics* 1, 863–923.
- Rotemberg, J. J. (1982). Sticky prices in the united states. *Journal of political economy* 90(6), 1187–1211.
- Zhang, L. (2005). The value premium. *Journal of Finance* 60(1), 67–103.