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# The Price of Delay: Supply Chain Disruptions, Pass-Through, and Firm Heterogeneity[1]

## Preliminary and Incomplete, Do Not Circulate

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**Abstract**

We study the firm-level pass-through of the supply chain shocks to consumer prices and the role of market structure using the model and a newly constructed dataset that integrates high-frequency, firm- and product-level data from U.S. imports and a consumer panel. We propose a novel approach to estimate the price effects of cost shocks and product availability. We then leverage unique Bill of Lading data, which provides transaction-level details about trade relationships, and consumer panel data from Numerator, which offers product-level price and sales information. Using the shift-share IV strategy, we find a sizable pass-through elasticity of delivery delays to consumer prices, especially if delays in import schedules are more protracted. Not all firms pass through shocks to prices the same way. Larger firms and those with higher market shares in their respective product categories show larger pass-through elasticities. Diversification in supply chains also matters. To quantify the importance of supply chain shocks, firm pass-through, and the role of market structure in the recent pandemic episode, we develop a quantitative framework where supply chain managers choose and manage supply chains, face competition, finite production capacity, and stochastic delivery delays along the supply chain.

KEYWORDS: Supply chains, Inflation, Delivery delays, Inventory, Firm heterogeneity, Pass-through
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# 1 Introduction

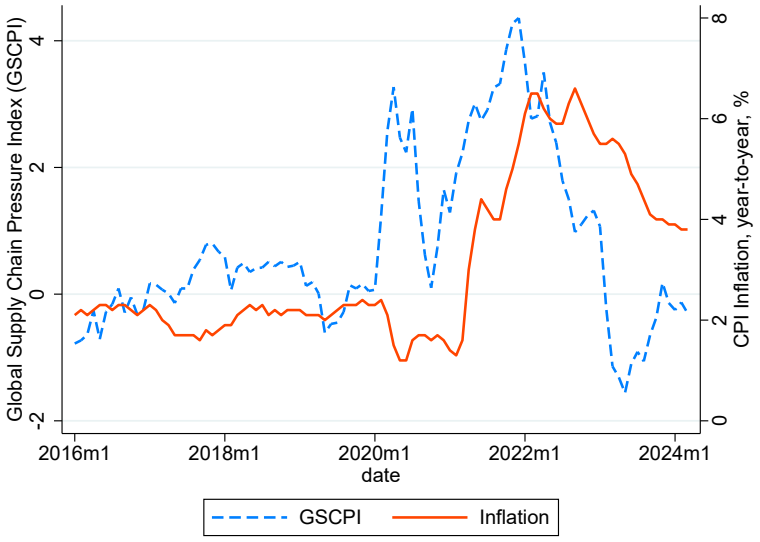
Throughout the pandemic, supply chain disruptions and their impact on inflation have been at the forefront of policy discussions. International trade and supply chains were disrupted in many different ways, ranging from backlogs at ports, heightened maritime shipping costs, production disruptions at the origin due to COVID restrictions, as well as increased demand shocks that put strains on limited production capacity. These various measures of disruptions are summarized by the NY Fed Global Supply Chain Pressure Index (GSCPI) depicted in blue in Figure 3. At the same time, US inflation has experienced historically high levels, as illustrated by CPI inflation depicted in Figure 3 in red. While the growing literature studies the implications of these supply chain disruptions (Ascari, Bonam and Smadu, 2024; Amiti, Itskhoki and Weinstein, 2024; Bai et al., 2024; Finck, Klein and Tillmann, 2024), it remains unclear what the firm-level pass-through of these disruptions to consumer prices is and what role market structure plays for the effect of shocks on consumer price dynamics.

To study these questions, we first derive the pass-through effects of product availability and supply chain disruptions onto prices in general equilibrium, providing us with an estimating framework. Next, we construct a new firm- and product-level dataset, building on the detailed transaction-level data on US imports and product-level transaction data from consumer purchases. We then estimate micro-level pass-through and study the role of firm heterogeneity. Finally, we propose a framework to quantify and aggregate firm-level pass-through estimates.

The paper proceeds in four steps. The theoretical framework extends the standard price-setting model by incorporating an endogenous costly inventory decision that directly influences product availability. In this setting, firms determine not only their log prices $p_{it}$ but also an availability shifter $\tau_i$ that serves as a proxy for inventory choices—such as order size, order frequency, and timing of inventory reviews—which together determine effective product availability. The model maintains the core accounting identity $p_{it} \equiv mc_{it} + \mu_{it}$ while linking inventory decisions with effective firm revenue, so that better product availability reduces competitive pressure and impacts the firm's pricing strategy.

Crucially, the framework yields a reduced–form equation that decomposes observed price changes into responses to cost shocks and availability shocks—capturing e.g. supply chain disruptions—while also quantifying strategic complementarities in these dimensions. In equilibrium, optimal pricing and inventory decisions are jointly determined via fixed–point relations, leading to an expression for the optimal markup in terms of the perceived demand elasticity $\sigma_i$. This elasticity aggregates the firm's own price sensitivity and the strategic feedback effects from competitors' pricing and inventory adjustments. The reduced–form equation thus allows for empirical estimation of the pass–through elasticities of both cost and availability shocks, as well as the strength of strategic interactions, even when direct measures

of marginal costs are unavailable.




*Notes*: (A) Global Supply Chain Pressure Index (GSCPI, NY Fed). (B) CPI for All Urban Consumers: all items less food and energy, year-to-year change, from BLS. (FRED, CPILFESL)

In the second step, we construct a micro-level dataset of delivery delays and consumer price changes at the firm and product levels by integrating two large-scale data sources. To measure supply chain pressures, we use Bill of Lading (BoL) data from S&P Global via the Panjiva platform. This dataset provides high-quality, high-frequency information on U.S. imports, capturing detailed economic and logistical aspects of maritime trade relationships at both the transaction and firm levels from 2007 to 2023. The availability of granular shipment-level data allows us to construct proxies for delivery delays at the firm-to-firm and firm-product-to-firm levels. We define delivery shortfalls at the firm and product-category level as deviations in the $k$-week moving average of monthly import volumes relative to the baseline levels before the disruptions in 2019. Our measures show significant shortfalls in imports in the 2020-2022 period. These shortfalls in imports widely differ across product categories and across firms within the same categories.

We use newly available Numerator Consumer Panel data for the period 2018-2023 to measure prices, availability, and sales of various products by firms. Data tracks millions of consumer purchases in brick-and-mortar and online stores and provides a wide coverage of stores and types of products as well as consumer demographics.[2]. The weighted aggregate spending in Numerator closely tracks the retail sales data from the Census, asserting the quality of data coverage. We define a product as the firm-brand-product category tuple and construct product-level 12-month price changes as our baseline measures of price changes. The inflation patterns suggested by Numerator prices closely resemble those indicated

[2]Data cover more than 50 million items from a billion of receipts from thousands of stores

by CPI. The granularity of Numerator price data provides us with initial insights into the firm-level dimension of price dynamics during the recent pandemic episode. Similar to delivery shortfalls, we observe significant variability in price increases across different product categories and among firms within those categories.

We match firm- and product-level delivery shortfalls from BoL with price changes constructed from Numerator to directly analyze the impact of supply chain disruptions on consumer prices.

We begin the analysis of our matched microdata by documenting firm-level heterogeneity in price changes during the recent inflationary episode. Firms increased prices at widely different rates, but larger firms, on average, increased their product prices more. The average inflation coming from high-market share firms- those in the top quartile of sales distribution in respective product categories- is 18% higher than that of smaller firms during the peak inflation in 2022. Conditional on size, the firms sourcing from more countries generally showed lower price growth- perhaps indicating that the reliance on more suppliers mitigated the firm-level exposure to supply chain disruptions.

We then move to identifying the pass-through of delivery delays to consumer prices. Our empirical strategy combines baseline OLS regressions with a shift-share instrumental variable (IV) approach designed to isolate exogenous supply-side shocks, allowing us to quantify how much of the observed price changes can be attributed to international delivery shortfalls while filtering out confounding demand-side factors. Our IV results indicate that delivery shortfalls lead to significant consumer price increases. Pass-through to prices is higher if firms face longer delivery shortfalls. The firms with higher market power exhibit a greater ability to pass on supply chain-related costs to consumers, highlighting the critical role of market structure in determining the impact of supply chain disruptions on price dynamics.

Finally, to quantify the aggregate importance of the delays for inflation during the COVID-19 pandemic, we build a quantitative model that allows for such aggregation. We build a model where agents make sourcing choices subject to finite production and fulfillment capacity. To make the model tractable, we incorporate insights from queuing theory into a workhorse trade model with supply chain choice (Antràs and Gortari, 2020). The model allows to build an index that traces out inflation pressure from delivery delays. We find that X% of price changes during the 2020-2023 period are attributed to the pass-through of delivery shortfalls to prices. To evaluate the role of market structure for aggregate price dynamics, we calculate the counterfactual price changes in the economy with equal market share distribution across firms. Other things equal, inflation is X% lower in a more competitive environment relative to the existing market structure in the economy. [tbd]

This paper contributes to the extensive literature on pass-throughs in the context of internationally sourcing firms. For example, Jan De Loecker, Pinelopi K Goldberg, Amit K Khandelwal and Nina Pavcnik

(2016) explored the effects of trade liberalization, finding that input tariff reductions substantially lower marginal costs but result in higher markups, leading to incomplete pass-through to prices and suggesting short-term benefits for producers over consumers. Amiti, Itskhoki and Konings (2019) have documented the importance of strategic complementarities in price setting, showing that large firms adjust their prices significantly in response to competitor price changes and cost shocks, while small firms do not respond to competitors' pricing but exhibit the complete pass-through of shocks to prices, which influences aggregate markup dynamics and exchange rate pass-through.

Lafrogne-Joussier, Martin and Mejean (2023) provided evidence on energy price shocks, demonstrating full pass-through of cost increases but only partial pass-through of cost reductions, with a limited overall impact on inflation due to energy's small share in variable costs and substantial within-industry heterogeneity. Our paper adds to this literature by focusing on the pass-through of delivery delays into prices, highlighting a distinct qualitative mechanism where supply chain disruptions, rather than input or energy cost changes, drive price adjustments, providing new insights into the dynamics of price setting in globally integrated markets.

A growing body of literature examines the implications of supply chain disruptions during the COVID-19 pandemic, focusing on the effect of these shocks on inflation and economic dynamics. Using Federal Reserve Bank of Atlanta's Business Inflation Expectations survey, Meyer, Prescott and Sheng (2023) document that supply chain disruptions shifted expectations and risks over firms' future unit costs. Comin, Johnson and Jones (2023) develop a New Keynesian framework showing that binding capacity constraints for domestic and foreign producers shift price Phillips Curves upward, amplifying inflationary pressures, particularly in the goods sector, and highlighting the role of loose monetary policy in fueling the inflation surge in 2021-2022. Similarly, Xiwen Bai, Jesús Fernández-Villaverde, Yiliang Li and Francesco Zanetti (2023) construct an index of global supply chain disruptions using data from container ship movements, demonstrating that supply chain shocks were a major driver of inflation in 2021, with traditional demand and supply factors gaining prominence in 2022. They further show that monetary policy is more effective in controlling inflation following a supply chain shock than under normal circumstances. Mary Amiti, Sebastian Heise, Fatih Karahan and Ayşegül Şahin (2024) also studied a DSGE model to quantify the effects of the supply chain, labor market disruptions, a shift from services to goods in consumption, and accommodative monetary policy on inflation.

Our paper adds to this literature by providing novel micro-data that identifies the causal effects of supply chain disruptions on inflation, specifically linking these effects to sourcing disruptions and delivery delays, offering a unique perspective on the qualitative channels through which supply chain shocks propagate.

The remainder of this paper is structured as follows: Section 2 introduces a simple model where firms conduct inventory management facing delivery delays, Section 3 introduces the data, provide stylized facts on price changes and delivery delays. Section 4 covers our analysis of pass-throughs from delivery delays to price changes. Section 5 introduces our framework for quantification, and Section 6 concludes.

# 2 Theory

In this section, we extend the non-parametric approach to characterizing optimal price setting taking strategic complementarities into account Amiti, Itskhoki and Weinstein (2024), to allow for an endogenous inventory choice that determines product availability and a (stochastic) revenue variable.

**Price setting with inventory management.** We begin with an accounting identity for the log price of firm $i$ in period $t$, which is expressed as the sum of the firm's log marginal cost, $mc_{it}$, and its log markup, $\mu_{it}$. That is,

$$p_{it} \equiv mc_{it} + \mu_{it}\,.$$

This identity not only defines a firm's realized log markup but also provides a framework for decomposing observed price changes into components attributable to changes in marginal cost and adjustments in pricing strategy. In empirical applications, where precisely measured marginal costs are typically unobserved, such a decomposition is invaluable because it permits the estimation of markups using observed price data. In the environment we consider, the firm's pricing decision is intertwined with its decision regarding product availability. In particular, firms choose not only their log price $p_i$ but also a stock-in probability shifter, $\tau_i$, which affects the effective stock–in probability through the function $s_i(q_i, \tau_i)$, where $q_i$ denotes the log demand faced by the firm. This function shifts the effective availability of the product, with higher values of $s_i$ implying better product availability and, hence, higher realized sales.

The firm's overall objective is to maximize an expression of the form

$$\exp\Big\{p_i + q_i\big(p_i, \boldsymbol{p}_{-i}, \tau_i, \boldsymbol{\tau}_{-i}; \xi\big) + s_i\big(q_i, \tau_i\big)\Big\} - TC_i\Big(\exp\big\{q_i\big(p_i, \boldsymbol{p}_{-i}, \tau_i, \boldsymbol{\tau}_{-i}; \xi\big)\big\}, \tau_i\Big),$$

where $\boldsymbol{p}_{-i}$ and $\boldsymbol{\tau}_{-i}$ denote the vectors of competitors' log prices and stock-in shifter decisions respectively, and $\xi$ collects the relevant demand shifters. The inclusion of the term $s_i(q_i, \tau_i)$ in the exponent captures the idea that the effective stock–in probability, which influences consumer choice through improved product availability, plays a crucial role in determining revenue. In our framework, we consider

an arbitrary invertible demand system $q_i = q_i(p_i, \boldsymbol{p}_{-i}, \tau_i, \boldsymbol{\tau}_{-i}; \xi)$, which ensures that each vector of prices and shifter decisions corresponds uniquely to a vector of quantities demanded. This assumption, though it rules out the special case of perfect substitutes, is mild and is consistent with many widely used demand specifications, including CES, linear, translog, and discrete-choice logit formulations.

The analysis is carried out at the level of the firm–product and accommodates various market competition structures ranging from monopolistic competition—where firms do not internalize the impact of their actions on industry–wide outcomes—to oligopolistic settings where strategic interdependence is paramount. Under full–information simultaneous–move games, the firm's pricing and availability decisions are determined by solving a static profit–maximization problem, where strategic effects are captured by a general conjectural variation function. This function, denoted by $h_{-i}(p_i, \tau_i, \boldsymbol{p}_{-i}, \boldsymbol{\tau}_{-i}; \xi)$, formalizes the firm's beliefs regarding the responses of competitors to changes in its own price and stock–in shifter. Crucially, this setup allows us to characterize the firm's optimal decisions in terms of two functions: a markup function that governs the optimal pricing decision and a stock–in premium function that determines the optimal adjustment of the stock–in shifter.

The markup function emerges from the equilibrium condition obtained by differentiating the firm's objective with respect to its log price. After accounting for the direct effect of a price change on revenue—augmented by the sensitivity of effective availability—and incorporating the effect of marginal cost and strategic interactions, the resulting first–order condition can be rearranged into the familiar form $e^{-\mu_{it}} = \frac{\sigma_i - 1}{\sigma_i}$, so that the firm's optimal markup is given by $\mu_{it} = \ln\left(\frac{\sigma_i}{\sigma_i - 1}\right)$. Here, the generalized perceived elasticity $\sigma_i$ reflects not only the own–price sensitivity of demand, adjusted for the responsiveness of effective availability through the derivative $\kappa_i = \partial s_i / \partial q_i$, but also the strategic effects arising from competitors' pricing and availability decisions. In particular, $\sigma_i$ is affected by the degree to which the firm's own price influences rivals' actions, as captured by the conjectural variation derivatives with respect to both $p_i$ and $\tau_i$. The markup function, $\mathscr{M}_i(\cdot)$, thus encapsulates the optimal adjustment in price above marginal cost as a function of the prevailing market environment. Figure 1b illustrates the firm's problem seeking to equate both marginal cost and marginal revenue, both of which are now endogenous and depend on the availability decisions and the perceived demand elasticity.

Similarly, the firm's decision regarding the stock–in shifter is characterized by differentiating the objective with respect to $\tau_i$. The derivative of the revenue function with respect to $\tau_i$ incorporates both the direct impact of the shifter on demand—as measured by $\eta_i = \partial q_i / \partial \tau_i$ and the direct effect of the shifter on effective availability, captured by $\kappa_i^{\tau} = \partial s_i / \partial \tau_i$—as well as strategic responses captured by the corresponding conjectural variation derivatives. After incorporating the (log) marginal cost associated with adjusting the stock–in shifter, $mc_{it}^{\tau}$, the first–order condition can be manipulated to yield a

fixed–point representation of the form $e^{-\mu_{it}} = 1 - \frac{mc^{\tau}_{it}}{\phi_i}$, so that the optimal stock–in premium is given by $\mathscr{T}_i(\cdot) = -\ln\left(1 - \frac{mc^{\tau}_{it}}{\phi_i}\right)$. The effective stock–in elasticity, $\phi_i$, aggregates the direct sensitivity of demand to changes in the shifter—adjusted for the impact on effective availability—and the strategic effects resulting from competitors' shifter adjustments. Thus, the stock–in premium function captures the extent to which the optimal stock–in shifter exceeds its marginal–cost benchmark, reflecting both the benefits of increased product availability and the interdependent responses of rival firms.

Under the minimal assumptions on demand and market structure outlined above, we obtain a characterization of the firm's static profit–maximizing decisions as fixed–point equations. The proposition below formalizes the result:

**Proposition 1.** *For any given invertible demand system and competition structure in prices and stock-in probability shifters, there exist a markup function $\mathscr{M}_i(\cdot)$ and a stock-in premium function $\mathscr{T}_i(\cdot)$ such that the firm's static profit-maximizing log price $\tilde{p}_{it}$ and stock-in shifter $\tilde{\tau}_{it}$ satisfy*

$$\tilde{p}_{it} = mc_{it} + \mathscr{M}_i\left(\tilde{p}_{it}, \tilde{\tau}_{it}, \boldsymbol{p}_{-it}, \boldsymbol{\tau}_{-it}; \xi_t\right), \tag{1}$$

$$\tilde{\tau}_{it} = mc^{\tau}_{it} + \mathscr{T}_i\left(\tilde{p}_{it}, \tilde{\tau}_{it}, \boldsymbol{p}_{-it}, \boldsymbol{\tau}_{-it}; \xi_t\right) \tag{2}$$

The optimal log price, $\tilde{p}_{it}$, and stock-in shifter, $\tilde{\tau}_{it}$, are the solutions to the above equations. These fixed–point relations capture the firm's best response in both dimensions and hold for any given vector of competitors' prices and stock–in shifters. In equilibrium, when every firm in the industry satisfies these conditions, the entire vector of prices and stock–in shifter decisions constitutes a consistent outcome of the underlying strategic game.

The extended characterization of firm behavior generalizes the traditional markup function result by incorporating product availability considerations through the stock–in shifter and its corresponding premium function. The optimal markup, $\mu_{it}$, depends on both the firm's own price and the prevailing competitive environment, while the stock–in premium, $\mathscr{T}_i(\cdot)$, reflects the interplay between demand sensitivity to availability and the cost of shifting the stock–in probability. This unified framework therefore provides a basis for empirical work in which price changes and product availability adjustments are jointly analyzed, even when direct measures of marginal cost are not observed.

**Price Change and Stock-In Shifter Change Decomposition** To derive an estimating equation for changes in the firm's price and stock–in shifter, we totally differentiate the firm's best response conditions around an admissible point—say, an equilibrium characterized by $\left(\tilde{p}_{it}, \tilde{\tau}_{it}, \boldsymbol{p}_{-it}, \boldsymbol{\tau}_{-it}; \xi_t\right)$.

A total differentiation of the best response condition (1) yields an expression for the differential

change in the firm's log price:

$$dp_{it} = dmc_{it} + \frac{\partial \mathcal{M}_i}{\partial p_{it}} dp_{it} + \frac{\partial \mathcal{M}_i}{\partial \tilde{\tau}_{it}} d\tilde{\tau}_{it} + \sum_{j \neq i} \frac{\partial \mathcal{M}_i}{\partial p_{jt}} dp_{jt} + \sum_{j \neq i} \frac{\partial \mathcal{M}_i}{\partial \tilde{\tau}_{jt}} d\tilde{\tau}_{jt} + \sum_{j=1}^{N} \frac{\partial \mathcal{M}_i}{\partial \xi_{jt}} d\xi_{jt}. \quad (3)$$

The markup function $\mathcal{M}_i(\cdot)$ is defined for any arbitrary vector of firm $i$'s own price and stock–in shifter, as well as those of its competitors. Hence, the above total–differentiation expression characterizes all possible perturbations to firm $i$'s optimal price in response to shocks to its own marginal cost ($dmc_{it}$), its own price ($dp_{it}$) and stock–in shifter ($d\tau_{it}$), as well as to competitors' prices ($dp_{jt}$) and stock–in shifters ($d\tau_{jt}$), and to changes in demand shifters ($d\xi_{jt}$). Notably, shocks to competitors' marginal costs are reflected in their observable price and stock–in adjustments, which serve as sufficient statistics; therefore, firm $i$'s pricing response depends on these aggregate observable changes rather than directly on competitors' unobserved cost shocks.

Solving the fixed point for $dp_{it}$ in (3) results in the following price change decomposition:

$$dp_{it} = \frac{1}{1+\Gamma_{it}} dmc_{it} - \frac{\Lambda_{it}}{1+\Gamma_{it}} d\tilde{\tau}_{it} + \frac{\Gamma_{-it}}{1+\Gamma_{it}} dp_{-it} + \frac{\Lambda_{-it}}{1+\Gamma_{it}} d\tilde{\tau}_{-it} + \varepsilon_{it}. \quad (4)$$

where the residual $\varepsilon_{it} \equiv \frac{1}{1+\Gamma_{it}} \sum_{j=1}^{N} \frac{\partial \mathcal{M}_i(\boldsymbol{p}_t, \boldsymbol{\tau}_t; \xi_t)}{\partial \xi_{jt}} d\xi_{jt}$ captures firm $i$'s effective demand shock. Here, we define the own markup elasticities with respect to the firm's own price and stock–in shifter as

$$\Gamma_{it} \equiv -\frac{\partial \mathcal{M}_i}{\partial p_{it}} \quad \text{and} \quad \Lambda_{it} \equiv -\frac{\partial \mathcal{M}_i}{\partial \tau_{it}},$$

and the cumulative competitor elasticities as

$$\Gamma_{-it} \equiv \sum_{j \neq i} \frac{\partial \mathcal{M}_i}{\partial p_{jt}} \quad \text{and} \quad \Lambda_{-it} \equiv \sum_{j \neq i} \frac{\partial \mathcal{M}_i}{\partial \tau_{jt}}.$$

Thus, the denominator $1 + \Gamma_{it}$ measures the overall sensitivity of firm $i$'s markup to changes in its own strategic variables (price and stock–in shifter), while the numerator $\Gamma_{-it}$ and $\Lambda_{-it}$ aggregates the impact of competitors' price and inventory adjustments. Importantly, these observable competitor changes serve as sufficient statistics for their unobserved cost shocks. A similar decomposition can be derived for the optimal stock–in shifter, jointly capturing the strategic interdependence in both pricing and inventory management.

Finally, $dp_{-it}$ and $d\tau_{-it}$ from equation (4) are defined the following way. The (scalar) index of competitor price changes, $dp_{-it}$, is defined as

$$dp_{-it} \equiv \sum_{j \neq i} \omega_{ijt}\, dp_{jt}, \quad \text{where} \quad \omega_{ijt} \equiv \frac{\partial \mathcal{M}_i(\boldsymbol{p}_t, \boldsymbol{\tau}_t; \xi_t)/\partial p_{jt}}{\sum_{k \neq i} \partial \mathcal{M}_i(\boldsymbol{p}_t, \boldsymbol{\tau}_t; \xi_t)/\partial p_{kt}}. \tag{5}$$

In our extended framework, where firms choose not only prices but also stock–in shifters, a similar index $d\tau_{-it}$ can be constructed for competitor stock–in changes. Specifically, the competitor stock–in shifter index is defined as

$$d\tau_{-it} \equiv \sum_{j \neq i} \omega^{\tau}_{ijt}\, d\tau_{jt}, \quad \text{where} \quad \omega^{\tau}_{ijt} \equiv \frac{\partial \mathcal{M}_i(\boldsymbol{p}_t, \boldsymbol{\tau}_t; \xi_t)/\partial \tau_{jt}}{\sum_{k \neq i} \partial \mathcal{M}_i(\boldsymbol{p}_t, \boldsymbol{\tau}_t; \xi_t)/\partial \tau_{kt}}.$$

These expressions imply that, regardless of the specific demand or competition structure, there exists a theoretically well-defined index for both competitor price changes and competitor stock–in shifter changes—even in cases where the demand system does not admit an ideal price (or delay) index (as under non-homothetic demand). In each index, the individual changes from competitors (whether $dp_{jt}$ or $d\tau_{jt}$ for $j \neq i$) are aggregated using endogenous, firm–state–specific weights that sum to one. The weights depend on the sensitivity of firm $i$'s markup to changes in competitors' strategic decisions: the larger the effect of a competitor $j$'s change on firm $i$'s markup, the greater the weight $\omega_{ijt}$ (or $\omega^{\tau}_{ijt}$) assigned to that competitor's adjustment in the aggregate index. This combined approach captures the full competitive environment in which both prices and product availability jointly influence firm $i$'s optimal decisions.

Equation (5) generalizes the accounting framework for price changes used in Amiti, Itskhoki and Weinstein (2024) by decomposing firm $i$'s price change into responses to its own marginal cost shock ($dmc_{it}$), its own inventory (stock–in) change ($d\tau_{it}$), competitors' price changes ($dp_{-it}$), and competitors' inventory adjustments ($d\tau_{-it}$); the residual $\varepsilon_{it}$ captures demand–side shocks.

To empirically estimate our theoretical price decomposition in equation (4) —which now augments the traditional framework to include both price changes and stock-in (inventory) adjustments—we must measure not only the competitor price index but also a competitor delay (or stock-in shifter) index. We now provide conditions under which the weights in these indices can be easily measured in the data. Let $z_t$ denote the log industry expenditure function, which quantifies the cost of purchasing one unit of aggregate output in a given industry. In our augmented model, product availability is explicitly incorporated via a stock-in adjustment function $s(\tau_t)$, so that the effective cost of consumption depends on both prices and availability. The following proposition summarizes this:

**Proposition 2.** *If the log expenditure function $z_t$ is a sufficient statistic for competitor prices and stock-in probabilities, i.e. if the demand can be written as $q_{it} = q_i(p_{it}, z_t; \xi_t)$, then the weights in the competitor price index (6) are proportional to the competitor revenue market shares $S_{jt}$, for $j \neq i$, and given by*

$\omega_{ijt} \equiv S_{jt}/(1-S_{it})$. *Therefore, the index of competitor price changes simplifies to:*

$$\mathrm{d}p_{-it} \equiv \sum_{j\neq i} \frac{S_{jt}}{1-S_{it}}\, \mathrm{d}p_{jt} \qquad d\tau_{-it} \equiv \sum_{j\neq i} \frac{S_{jt}}{1-S_{it}} d\tau_{jt}.$$

These results imply that, independently of the specific demand and competition structure, there exist theoretically well-defined indices of competitor price changes and competitor inventory adjustments. In our augmented framework, these indices jointly capture the external influences on a firm's optimal price, allowing us to decompose its price change into responses to its own marginal cost shock, to competitors' price changes, and to competitors' inventory (stock-in shifter) adjustments, with the weights determined endogenously by the competitors' revenue shares.

The intuition for this proposition is as follows. In our extended model, the log expenditure function is designed to capture not only the cost of purchasing output at given prices but also the effect of product availability, as reflected by stock-in probabilities. This function aggregates the information contained in both competitor prices and inventory decisions into a single index that consumers use to evaluate the overall cost of obtaining the industry output. Under the assumption of a nested-CES demand structure or symmetric preferences, this aggregate expenditure measure acts as a sufficient statistic for the entire competitor vector. In other words, from the consumer's viewpoint, the complex array of competitor prices and availability levels is fully summarized by the log expenditure function, meaning that the detailed distribution of competitors' strategic choices can be effectively replaced by this aggregate index.

Building on this, the Envelope Theorem ensures that when we differentiate the minimized expenditure function with respect to the product availability adjustment, only the direct effect remains while all indirect effects (through changes in the optimal quantities) cancel out. This means that the marginal impact of a change in product availability on the aggregate expenditure is precisely equal to the firm's revenue market share. Extending this insight using the chain rule, we find that the sensitivity of the markup function to a competitor's stock-in shifter can be expressed in terms of that competitor's market share. Consequently, when constructing a competitor delay index—which aggregates competitors' stock-in shifter changes—the weight assigned to each competitor is proportional to its revenue share relative to the rest of the market. This result implies that both competitor price and inventory effects on a firm's optimal decision can be summarized in a unified manner by observable market shares, greatly simplifying the empirical analysis.

As a result of Proposition 2, we can write an empirical counterpart of the theoretical price decomposition in (4) as:

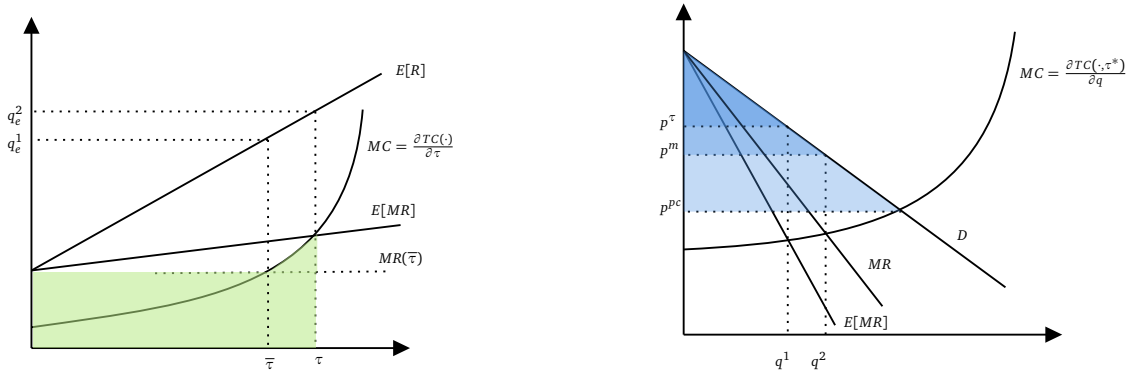
$$dp_{it} = \alpha_{it} dmc_{it} - \beta_{it} d\tau_{it} + \gamma_{it} dp_{-it} + \delta_{it} d\tau_{-it} + \varepsilon_{it}. \tag{6}$$

where $dp_{-it}$ and $d\tau_{-it}$ are competitors' market share-weighted price and inventory changes as defined in Proposition 2, and the coefficients are defined as:

$$\alpha_{it} \equiv \frac{1}{1+\Gamma_{it}} \qquad \beta_{it} \equiv \frac{\Lambda_{it}}{1+\Gamma_{it}} \qquad \gamma_{it} \equiv \frac{\Gamma_{-it}}{1+\Gamma_{it}} \qquad \delta_{it} \equiv \frac{\Lambda_{-it}}{1+\Gamma_{it}}$$

Here, $\alpha_{it}$ measures the firm's own (idiosyncratic) cost pass–through—- the elasticity of its price with respect to its marginal cost. The coefficient $\beta_{it}$ measures the firm's own inventory pass-through– the elasticity of its price with respect to its own stock–in shifter, holding competitors' actions constant. The coefficient $\gamma_{it}$ measures the strength of strategic complementarities in price setting, while $\delta_{it}$ captures the effect of competitors' inventory (stock–in) adjustments. A higher own markup elasticity to prices (i.e. a larger $\Gamma_{it}$) reduces $\alpha_{it}$ and $\beta_{it}$, implying more accommodative markups. Also note that markup elasticity to own price and stock-in shifter interact to determine the pass-through of stock-ins to prices. Higher competitor elasticities (larger $\Gamma_{-it}$ and $\Lambda_{-it}$) increase the responsiveness of firm $i$'s price to rivals' strategic actions.

**Figure 1.** Inventory management with delivery delays: Monopolist




**(a)** Inventory Management **(b)** Monopoly Pricing

**Notes**: Panel (a) illustrates the monopolist's inventory problem. Panel (b) illustrates the pricing problem from Equation (**??**).

**Structural Elasticities: Inventory Choice** To connect our theoretical framework to underlying microeconomic behavior, we derive explicit microfoundations for two key parameters: the perceived demand elasticity, $\sigma$, and the stock–in elasticity, $\kappa$. The perceived demand elasticity, $\sigma$, aggregates the direct price responsiveness of demand with the impact of product availability—measured by the stock–in elasticity $\kappa$—and, in competitive settings, incorporates strategic interactions with rivals. These parameters play a central role in determining optimal markups and inventory policies.

In a monopolistic environment without strategic interactions, the firm faces isoelastic demand, $q(p) = Ap^{-\epsilon_i}$, where $\epsilon_i > 0$ denotes the own-price elasticity of demand. The firm reviews its inventory at endogenous intervals determined optimally, accounting for probabilistic delivery delays characterized by probability $q$ and duration $\Delta$. Hence, the effective replenishment cycle is $\tau + q\Delta$. The expected inventory run–down time is $\tau_Q = Q/\pi$, with $\pi$ representing the consumption rate, and the fraction of time the product is stocked is defined as

$$s^* = \frac{Q/\pi}{\tau + q\Delta}.$$

We can map the framework that is being derived in more detail in the Appendix against the non-parametric model and do so formally in the proposition below.

**Proposition 3.** *Under isoelastic demand $q(p) = Ap^{-\epsilon_i}$ and an inventory review policy with delays such that $s^* = \frac{Q/\pi}{\tau+q\Delta}$, if the stock–in elasticity satisfies $\varepsilon_s = \kappa_i \epsilon_i$, the firm's static profit-maximizing price satisfies*

$$\tilde{p}_{it} = mc_{it} + \mathscr{M}_i\Big(\tilde{p}_{it}, s^*, \boldsymbol{p}_{-it}; \xi_t\Big),$$

*with effective demand elasticity*

$$\sigma = \epsilon_i(\kappa_i + 1),$$

*implying that the optimal markup is*

$$\frac{\tilde{p}_{it}}{mc_{it}} = \frac{\sigma}{\sigma - 1}.$$

This microfounded characterization explicitly aligns structural elasticity $\sigma$ in the parametric model with parameters governing the monopolistic firm's pricing and inventory decisions.

**Structural Elasticities: Strategic Interactions** In competitive markets, firms not only set prices and manage inventory but also interact strategically with rivals. To capture these dynamics, we extend the BEJK model by incorporating product availability via a Poisson thinning mechanism. In this setup, consumer arrivals follow a Poisson process, but only a fraction $s_i(\tau_i)$ of arrivals result in a sale due to stock–in considerations. Consequently, the effective competitor price is given by

$$p^*_{-i} = \mathbb{E}\Big[\min_{j \neq i}\{p_j - s_i(\tau_{it})\}\Big],$$

which adjusts rivals' posted prices by the firm's own stock–in probability. The extended BEJK model then implies that firm $i$'s perceived demand elasticity takes the form

$$\sigma_i = \epsilon_i(1+\kappa_i) - \zeta_i' Z_i^{-1}\delta_i - \theta_i' \Theta_i^{-1}\gamma_i.$$

Here, $\epsilon_i$ represents the baseline own–price elasticity, and $\kappa_i$ captures the responsiveness of availability to demand. The cross–elasticity terms, involving $\zeta_i$, $Z_i$, $\delta_i$, $\theta_i$, $\Theta_i$, and $\gamma_i$, reflect how competitors' pricing and stock–in adjustments feed back into firm $i$'s demand. Notably, a higher stock–in probability raises the effective competitor price, increasing $\sigma_i$ and lowering the optimal markup, while stronger strategic feedback from rivals works in the opposite direction.

**Proposition 4.** *Suppose consumers choose among varieties with idiosyncratic preference shocks and that the effective competitor price is defined by*

$$p_{-i}^* = \mathbb{E}\Big[\min_{j\neq i}\{p_j - s_i(\tau_{it})\}\Big].$$

*Then, the perceived demand elasticity for firm $i$ is given by*

$$\sigma_i = \epsilon_i(1+\kappa_i) - \zeta_i' Z_i^{-1}\delta_i - \theta_i' \Theta_i^{-1}\gamma_i.$$

*where the cross-elasticity terms depend on the stochastic availability of competitor products, i.e. $\zeta_i' \propto s_i(\tau_{it})$.*

Within this extended BEJK framework, the equilibrium markup distribution is shaped by both the direct effects of product availability and the indirect strategic interactions. Under standard assumptions, equilibrium markups may exhibit a Pareto tail, but the Poisson thinning mechanism—introduced through the stock–in probability—imposes an exponential damping that steepens the tail relative to models without such inventory considerations.

In summary, whether operating as a monopolist or in a competitive market, the structural elasticities $\sigma$ and $\kappa$ are central to understanding pricing and inventory decisions. In the monopolistic environment, solving for the optimal review interval $\tau$ in closed form directly links product availability to lower effective demand elasticity and reduced markups. In competitive settings, our extended BEJK model, with its incorporation of Poisson thinning via stock–in probabilities, illustrates how improved availability not only shifts the effective competitor price but also interacts with strategic feedback effects to determine an equilibrium markup distribution.

**Estimating Equation** We now extend our estimating equation to incorporate not only the effects of competitors' price and stock–in shifter changes on a firm's optimal price, but also the firm's own changes in its stock–in shifter. In this specification, the change in firm $i$'s log price over time is given by

$$\Delta p_{it} = \alpha \, \Delta mc_{it} + \beta \, \Delta \tau_{it} + \gamma \, \Delta p_{-it} + \delta \, \Delta \tau_{-it} + \varepsilon_{it} \, ,$$

where $\Delta p_{it}$ represents the change in firm $i$'s log price, and $\Delta mc_{it}$ its change in log marginal cost. The coefficient $\alpha$ captures the own cost pass-through—that is, the responsiveness of the firm's price to its own cost shock. The new term $\beta \, \Delta \tau_{it}$ reflects the direct impact of the firm's own stock–in shifter change on its price, capturing the role of product availability in the firm's pricing decision. In addition, $\gamma \, \Delta p_{-it}$ measures the sensitivity of firm $i$'s price to changes in competitors' prices, while $\delta \, \Delta \tau_{-it}$ quantifies the effect of competitors' inventory (stock–in shifter) adjustments on firm $i$'s price. The residual $\varepsilon_{it}$ aggregates demand–side shocks not captured by these variables.

The underlying assumption here is that the augmented log expenditure function—incorporating both prices and product availability—is a sufficient statistic for the competitive environment. This means that, from the consumer's perspective, all relevant information in the competitors' price and stock–in shifter vectors is summarized by the expenditure function. Using the Envelope Theorem, we can show that the marginal effect of a competitor's stock–in shifter on the expenditure function is proportional to that competitor's market share. Consequently, the weight on competitor $j$'s inventory change in the competitor delay index is given by its market share relative to the rest of the industry. This same logic applies to the competitor price index. In our estimating equation, the coefficients $\alpha$, $\beta$, $\gamma$, and $\delta$ collectively summarize the firm's response to its own cost and availability shocks as well as to competitors' strategic actions, providing a parsimonious yet comprehensive description of the pricing behavior in the industry.

## 2.1 Shortfall in Imports as a Proxy for Delivery Delays

In empirical analysis, directly measuring delivery delays poses a challenge because it requires information on both scheduled and actual delivery times; however, typically only the latter is available. As a result, we must infer delivery delays indirectly. The inventory model provides a framework for identifying these delays within import data by interpreting shortfalls in observed imports as a consequence of delivery delays.

Mathematically, the total volume of imports over a given time interval $t \in [0, T]$ can be modeled as:

$$\text{Imports}_{0,T} \equiv (T - p^d \cdot d) \times Q,$$

where $T$ represents the total available time for import activity within the period, $p^d \cdot d$ denotes the expected waiting time due to delivery delays, with $p^d$ as the probability of a delay and $d$ as the average duration of those delays, and $Q$ is the rate of order fulfillment or the quantity of goods scheduled to be delivered during the time interval. This relationship indicates that the effective time available for imports is reduced by the expected waiting time due to delivery delays ($p^d \cdot d$). As delivery delays increase, either through a higher probability ($p^d$) or longer duration ($d$), the effective time for importing decreases, leading to a reduction in the actual volume of imports.

From an economic perspective, the key insight is that delivery delays act as a friction that reduces the firm's ability to replenish inventories, directly impacting the observed import volumes. The effect of delays on imports can be further quantified by examining the elasticity of imports with respect to waiting time:

$$\frac{d \ln \text{Imports}_{0,T}}{d \ln d} = \frac{\partial \text{Imports}_{0,T}}{\partial d} \cdot \frac{d}{\text{Imports}_{0,T}} < 0.$$

This negative relationship demonstrates that an increase in the expected waiting time ($d$)—holding other factors constant—leads to a proportionate decline in the volume of imports. The magnitude of this decline depends on the sensitivity of import volumes to changes in delivery delays, capturing how critically the supply chain's reliability affects overall import activity.

Economically, using observed import shortfalls as a proxy for delivery delays provides a practical means of capturing supply chain disruptions in the absence of precise scheduling data. This approach leverages the theoretical prediction that as delays increase, import volumes systematically fall below their expected levels, reflecting the friction caused by unreliable deliveries. By controlling for other factors that influence imports, such as demand fluctuations or policy changes, we can isolate the effect of delays and use import shortfalls to empirically identify the extent of delivery disruptions. This method allows us to link supply chain performance directly to economic outcomes, such as inventory levels, production schedules, and market prices, providing valuable insights into the broader economic impacts of delivery delays.

# 3 Data Overview

We link two large-scale micro-level datasets not traditionally explored in economics research. The first dataset is a shipment-level bill of lading (BoL) data collected by U.S. ports and customs. It captures the universe of US imports (with some limitations explored by Flaaen et al. (2023)) and provides economic and logistical details about the shipments. We use this dataset to measure supply chain pressures and transportation delays. The second dataset provides product-level price and sales information from a unique consumer panel by Numerator, allowing us to track price changes at the most disaggregated – firm and product levels. We describe each dataset in more detail and outline the construction of the BoL delivery shortfalls and price changes in Numerator.

## 3.1 Bill of Lading Data (BoL)

The analysis relies on bill of lading (BoL) data to infer import quantities, prices, and delivery delays. A bill of lading is a critical legal document between the shipper and carrier required for the shipment of goods, detailing the commodity, shipping and receiving entities, vessel identifier, port of entry, payment terms, and specific logistics details. These data are derived from images of contracts processed from U.S. ports and customs, providing a unique, high-quality, high-frequency view of trade relationships at the transaction and firm level. The BoL data are advantageous for capturing detailed maritime trade and logistical information in a timely manner, making them well-suited for analyzing international delivery delays.[3]

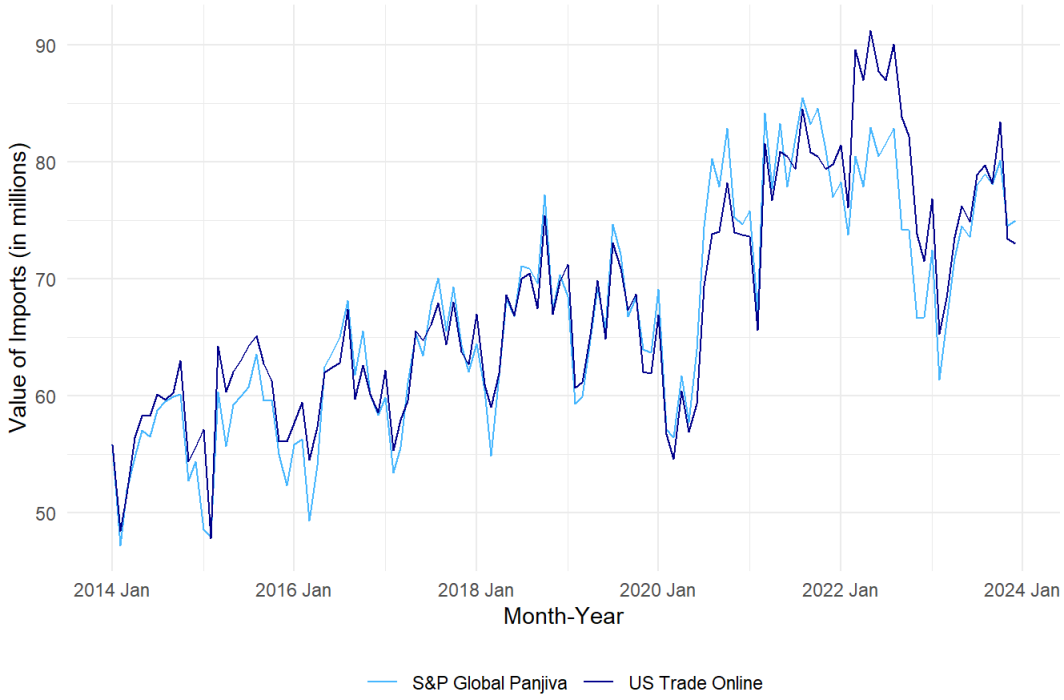
The BoL data used in this analysis are sourced from S&P Panjiva, which provides comprehensive records of U.S. imports since 2007, covering over a billion shipments from 17 different countries. Figure 2 compares imports in BoL against the maritime US imports in the Census. Since BoL does not provide reliable information on import values, we convert the import volumes of each HS code in 2019 to its import values in that year using Census volume-to-value conversion for each HS code in 2019. This way, the series in Figure 2 are benchmarked to equate the 2019 values, but the movements over time show that the series track each other pretty well, with some underestimation in BoL import value in 2022.[4]

The data granularity allows researchers to link shipment data to firm-level variables, enhancing the accuracy of empirical analysis. The data offer a unique opportunity to study delivery delays that manifest themselves in import shortfalls across U.S. importing firms by using the detailed shipment records available at the firm-to-firm-product level.

[3] In 2020, 43% of total US imports by value and 60% of imports by weight (Bureau of Transportation Statistics).

[4] It might be explained by the fact that BoL import series are using 2019 volume-to-value conversion, and in 2022, there has been a spike in import costs index as seen in Appendix Figure A.3.

**Figure 2.** US Imports over Time. Panjiva vs. Census




*Notes:* Aggregate imports in BoL Panjiva against USA Trade Online - U.S. Census Bureau imports data. Panjiva import volumes are indexed to the 2019 unit value of an HS code in Census data.

To isolate delivery delays, particularly those caused by port congestion and other specific disruptions, the analysis *will incorporate* additional data on port congestion and shipping delays. These complementary data sources, including Automatic Identification System (AIS) data that provide detailed vessel trajectories and port dwell times, help distinguish between delays due to port congestion and those specific to the shipment's origin, enhancing the identification strategy.

**Construction of Delivery Shortfalls.** Inspired by our discussion in Section 2.1, the core measure of interest, delivery shortfall, is constructed to quantify the deviations in import volumes relative to a baseline year, capturing the impact of delivery delays at the firm and product level. Specifically, monthly delivery shortfalls are calculated as the percent deviation of a $k$-week moving average of current imports from their 2019 levels, serving as a pre-disruption benchmark. The delivery shortfall at the firm-HS-code level is defined mathematically as:

$$\text{Delivery Shortfall}_{f,j,t(k)} = 2\frac{\sum_{m=t-k}^{t} D_{f,j,m} - \sum_{m=t-k,2019}^{t,2019} D_{f,j,m}}{\sum_{m=t-k}^{t} D_{f,j,m} + \sum_{m=t-k,2019}^{t,2019} D_{f,j,m}},$$

where $D_{f,j,m}$ represents the observed imports for firm $f$ and product $j$ in period $m$. The formula computes the difference between current imports and those in the baseline year (2019), normalized by the sum of both, providing a symmetric percent deviation measure that captures both increases and decreases in import volumes.

This firm-HS-code-level measure is then aggregated to obtain a firm-level delivery shortfall by weighting the HS-code shortfalls by their share in total imports:

$$\text{Delivery Shortfall}_{f,t(k)} = \sum_j s_{fj} \text{Delivery Shortfall}_{f,j,t(k)},$$

where $s_{fj}$ represents the share of each HS-code $j$ in the total imports of firm $f$. This aggregation captures the overall impact of delivery disruptions at the firm level, accounting for the relative importance of each product category in the firm's portfolio.

The chosen approach leverages the high dimensionality and granularity of BoL data to construct a robust proxy for delivery delays. By comparing current import volumes with pre-disruption levels, the shortfall measure effectively captures deviations attributable to shipping disruptions, production delays, and other logistical challenges. This measure is particularly valuable because it directly reflects firm-level disruptions in supply chains, making it suitable for analyzing the economic impact of delivery delays on firms' operations. Including additional data on port congestion and shipping delays further refines the analysis, allowing us to differentiate between delays caused by external factors and those specific to the origin or production side. [TBD] This comprehensive approach enhances the validity of the delivery shortfall measure, providing a meaningful proxy for disruptions of delivery schedules and import delays.

Notice that the change in delivery schedule can also be caused by aggregate or individual demand factors. In their raw form, delivery shortfall measures do not filter out these demand factors. In the regression analysis, we will include market-related trends to filter out aggregate demand factors and use the IV approach to filter out the individual demand forces.

Also, notice that the construction of the delivery shortfall measure relies on a somewhat stable sample of firms with some deliveries in 2019 and deliveries afterward. This implies that a sample of firms for which we have delivery delays has an attrition.[5]

XXX TALK ABOUT IMPORT PRICES HERE!

[5]This attrition can be seen in Figure **??**, which plots total import series similar to Figure 2 but for a sample of firms who have non-missing delivery shortfalls. This growing gap over time shows the importance of entry into BoL.

## 3.2 Numerator Data

We use consumer panel data from Numerator for the period 2019-2023 to infer prices, availability, and sales of various products by firms. Numerator is a marketing research company that collects data on consumer purchases in brick-and-mortar stores and online. Users of the Numerator app participate by either taking pictures of their receipts or passively sharing their digital purchases by allowing the app to track their online activity. These data have not yet been widely used in economics research.[6] The closest counterpart to these data is the widely used Nielsen Homescan (HMS) data from the Kilts Center. For our purposes, Numerator's advantages over HMS include its coverage of the recent pandemic period and its inclusion of e-commerce, whose share of total retail sales substantially increased since the pandemic. Appendix Section B.1 provides more details about the data.

Each shopping receipt recorded in the Numerator data provides detailed information about the purchased basket, including product descriptions, quantities purchased, prices, and details about the stores (such as name and address) where the purchases occurred. Each panelist also reports extensive demographic information, including age, gender, race, household characteristics, employment status, income bracket, and home address (metro area, postal code). Important for our analysis is the information on products. Where available, Numerator product IDs are linked with UPC/GTIN codes, brands, and producer names.[7] Products are classified into different categories with varying levels of aggregation. We exclude purchases that lack classification or are categorized as restaurants, non-items, or intermediate categories, focusing on product IDs with non-missing brand or manufacturer information.

Numerator data cover more than one billion receipts reported by 2.5 million users, including 400,000 static panelists who consistently report for at least 12 consecutive months and are representative of the U.S. population census. Approximately 90% of the transactions are from offline purchases, while the remaining transactions come from digital sites such as Amazon.com. The comparisons of Numerator data with other official statistics suggest that the data provide comprehensive coverage of product sales and consumer behavior in the U.S. First, the demographics of static panelists are similar to those reported in the 2019 Census, and the data include demographic weights that allow us to adjust variables further to be representative of the U.S. population. Second, changes in total sales across different purchase categories (such as apparel, electronics, health and beauty, and food) closely track the sales changes observed in U.S. Census Monthly Retail Sales data. Most importantly for our analysis, monthly price changes in Numerator closely align with monthly price changes reported by the BLS for various purchase categories.

[6] A version of the Numerator data from the Chicago Kilts Center Archive was recently used in He and Su (2023).
[7] Many products or services are not associated with UPC codes, such as restaurant or entertainment purchases.

For our baseline analysis, we aggregate 54 million item IDs reported in Numerator and define a product as the unique combination of the firm, brand, and product category. This approach yields 645,890 distinct products and 77,395 brands sold by 9,458 firms across 4,000 different product categories.[8]

For each product and month, we construct the median monthly price based on all transactions reported on the receipts from static users.[9] We calculate product sales as the total sales from the receipts of static users, weighted by the user's demographic weight and Numerator sales projections, yielding a product-month panel with sales and price information. This panel is then used to construct price changes over time.

Our baseline measure of product-level price change is a 12-month smoothed price change for product $p$ in month $t$, defined as:

$$\Delta_{12}\ \text{Price}_{p,t} = 2\frac{\text{Price}_{p,t} - \text{Price}_{p,t-12}}{\text{Price}_{p,t} + \text{Price}_{p,t-12}}.$$

This measure, inspired by Davis, Haltiwanger and Schuh (1998), reduces the influence of outliers and captures relative price changes over a one-year horizon, allowing for robust analysis of pricing dynamics. We verify the robustness of our results by comparing this smoothed measure with alternative growth definitions, confirming that our findings are consistent across different specifications.

### 3.3 BoL-Numerator Match

We match data from the Bill of Lading (BoL) with Numerator data by linking firm names from both datasets at the firm level. The matching process involves several decisions regarding the identification of firms in each dataset. For the BoL data, we primarily use consignee names as our main firm identifier. The consignee typically represents the entity receiving the goods, often corresponding to the U.S. importing firm or its designated representative. To capture cases where U.S. multinational firms directly ship products from abroad to U.S. stores, we also use shipper names from the BoL. Thus, our company identifiers from Panjiva are based on a combination of consignee and shipper names, allowing us to account for both direct imports and shipments managed through intermediaries.

In the Numerator data, each product is associated with several potential identifiers, including manufacturer names, parent brand names, and brand names. The manufacturer name serves as the primary identifier, but this information is often missing on scanned receipts, particularly for less prominent products. The data provider makes efforts to supplement missing manufacturer information for high-sales

[8] Examples of products include *Hewlett Packard/Hewlett Packard/Calculators*, *Revlon Consumer Products/Revlon/Flat Irons*, *American Italian Pasta Company/Mueller's/Lasagna*, and *Loreal/Cerave/Bar Soaps*.

[9] We also construct alternative measures, including average and sales-weighted average prices, with and without restricting to static users. These measures are highly correlated.

products, meaning that larger firms and popular brands are more likely to have complete manufacturer data, while it may be missing for smaller firms or less significant products.

To facilitate matching between the datasets, we first clean and standardize the company names collected from both sources to ensure consistency and comparability. The matching process starts from the Numerator data, where the unit of observation includes the manufacturer name, parent brand, and brand name for each product. We perform an exact match with BoL consignee and shipper names following a hierarchical matching order. The first step involves matching the manufacturer name from the Numerator with the consignee name in the BoL data. If no match is found, we proceed to match the parent brand name with the consignee names, and if still unmatched, we attempt to match the brand name with the consignee names. If none of these identifiers from the Numerator match with the consignee names, we extend the matching process to the shipper names in BoL, applying the same hierarchical order: starting with the manufacturer name, followed by the parent brand name, and finally, the brand name.

The matching process results in approximately half of the products in Numerator being successfully linked to the BoL data, covering 63% of total sales reported in Numerator. This outcome highlights the importance of detailed and accurate firm and brand information in establishing robust links between transaction-level data sources. To further refine the sample, we restrict our analysis to Numerator firms that have at least one recorded import during the sample period from 2018 to 2023. This restriction ensures that our analysis focuses on firms actively engaged in international trade, aligning with the primary objective of studying the impact of delivery delays and import shortfalls on product availability and pricing.

After applying these restrictions, our final dataset consists of 4.2 million product-month observations, representing 164,211 distinct products sold by 7,150 firms. This matched dataset provides a comprehensive and granular view of how international trade dynamics, such as delivery delays and import disruptions, affect firm-level pricing, sales, and product availability in the U.S. market.

# 4 Empirical Analysis

We empirically analyze the relationship between supply chain disruptions, import shortfalls, and inflation. First, we document stylized facts on inflation and import shortfalls, highlighting the variations across sectors and firms using Numerator and BoL data. We also provide evidence on which firms during the pandemic experienced the biggest growth in product prices. Next, we identify firm-level pass-through of delivery shortfalls to prices, employing OLS and shift-share IV strategies to isolate ex-

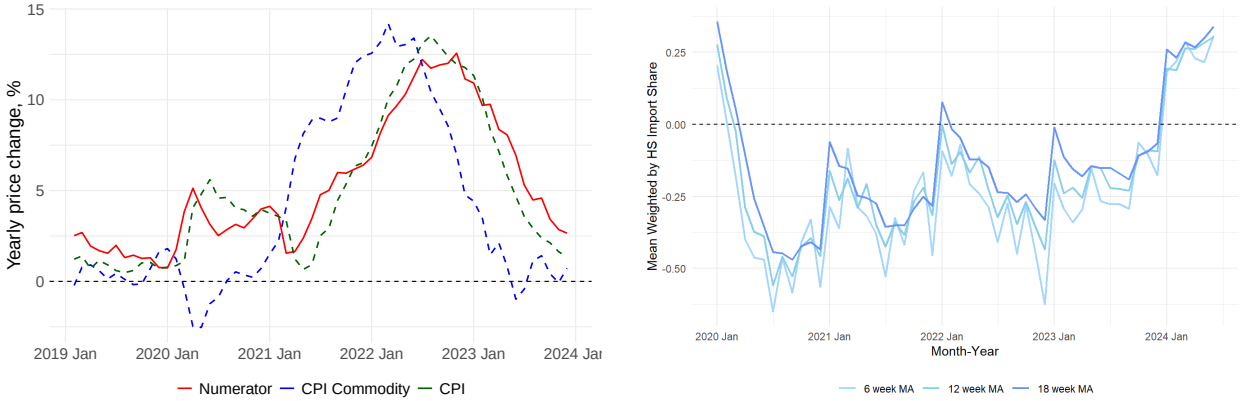
ogenous supply-side shocks. Finally, we present evidence showing that firms with higher market power exhibit greater pass-through of supply chain disruptions to consumer prices, underscoring the role of market structure in shaping inflationary outcomes during the pandemic.

## 4.1 Stylized Facts on Inflation and Import Shortfalls

We begin our empirical analysis by documenting key stylized facts on inflation and import shortfalls using data from Numerator and Bill of Lading (BoL). Panel A of Figure 3 presents 6- and 12-month measures of inflation derived from Numerator data alongside the 12-month Urban CPI inflation from official statistics. The results show that price changes in Numerator closely track the trends observed in official CPI data, reaching their peak in mid-2022. This alignment indicates that Numerator data provides a reliable measure of consumer price inflation, capturing the broader inflationary pressures observed across the economy during the pandemic period.

**Figure 3.** Inflation and Import Shortfalls

(A) Numerator price growth vs CPI (B) Panjiva aggregate import shortfall




*Notes*: (A) Numerator data. Laspeyres index for static users, weighted with expenditure shares, demo weights, and trend factors. Removed outliers in produce-level price changes (1 percent, two-sided). Aggregated from product-level to category-level by median price, and further aggregated from category-level to basket by sales share weighted average. (B) BoL data. The average import shortfalls are constructed as a weighted mean of firm-level shortfalls (see equation (??)).

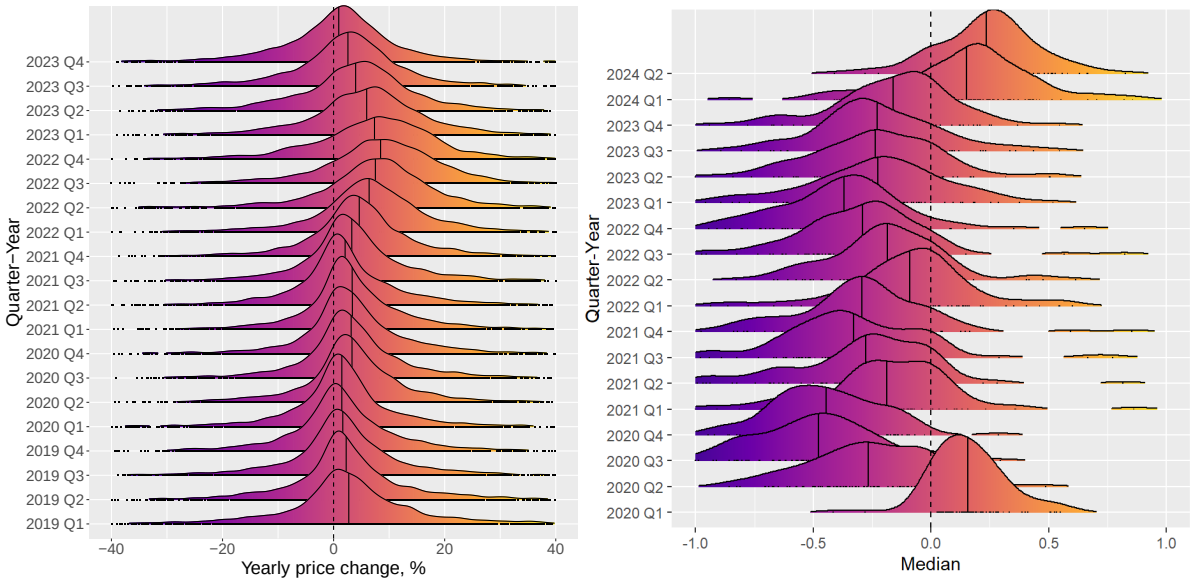
Panel B of Figure 3 illustrates the evolution of import shortfalls, defined as the percent deviation of the 18, 12, and 6-week moving averages of imports from their 2019 levels. These shortfalls reflect disruptions in supply chains, where higher deviations indicate more significant delays and interruptions in the flow of goods. The data reveal pronounced fluctuations in import shortfalls, highlighting the extent to which supply chain disruptions have contributed to economic volatility during the study period.

Figure 4 further explores the heterogeneity in price changes and import shortfalls across different sectors. Panel A shows the distribution of price changes across various product categories, revealing a

**Figure 4.** Sectoral Heterogeneity in Price Changes and Import Shortfalls

(A) Distribution of price changes (by category)

(B) Distribution of import shortfalls (by HS2 code)




*Notes*: (A) Distribution of annualized percent change in Prices by Category (12 Month Percent Change, averaged by quarter), constructed from median prices of the demographically weighted static sample, based on 1 percent trimmed micro sample, aggregated to department categories by median price. (Numerator, own calculations) (B) Import shortfalls constructed as mean level deviations in the same month compared to 2019 baseline, HS2 categories weighted with firm-level value shares (Census, Panjiva, own calculations)

rightward shift over time that indicates overall price growth. However, the distribution is not uniform; different sectors experienced distinct dynamics, with some categories showing sharp price increases while others remaining relatively stable. Panel B shows the variation in exposure to supply chain disruptions across different HS product codes, characterized by a long left tail of products facing severe import shortfalls. This evidence underscores that supply chain challenges did not impact all sectors equally, with some industries facing much more significant constraints than others.

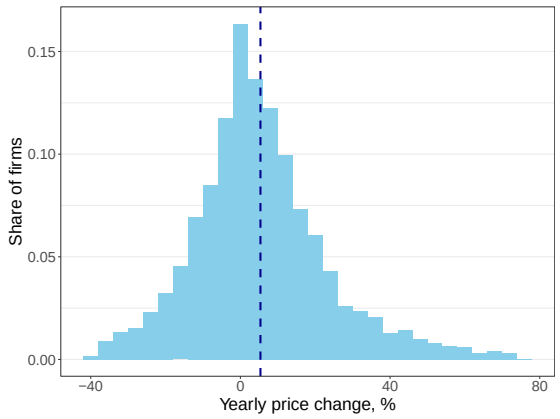
Lastly, Figure 5 demonstrates the variation in price changes and import shortfalls across firms, highlighting substantial heterogeneity at the firm level. The data show that firms experienced widely differing degrees of inflationary pressure and supply chain disruptions, reflecting the idiosyncratic nature of firm-level exposure to global supply chain challenges.

Which firms experienced the highest growth in prices? Figure 6 shows that larger firms and the ones with higher market shares in their respective product categories experienced the largest price hikes. Panel (A) presents a simple binscatter of the product-level 12-month price changes against log firm size, defined as the average yearly sales of the firm in Numerator, conditional on product department and year fixed effects. Panel (B) shows a similar binscatter but plotted against the firm market share in the product category, conditional on product department and yearfixed effects.

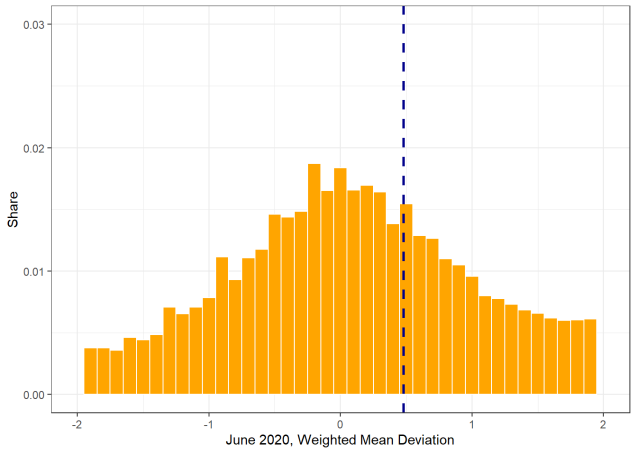
Figure 7 hints at the importance of supply chain diversification for firm price dynamics. In particular,

**Figure 5.** Firm-Level Heterogeneity in Price Changes and Import Shortfalls

(A) Distribution of price changes across firms




(B) Firm distribution of import shortfalls



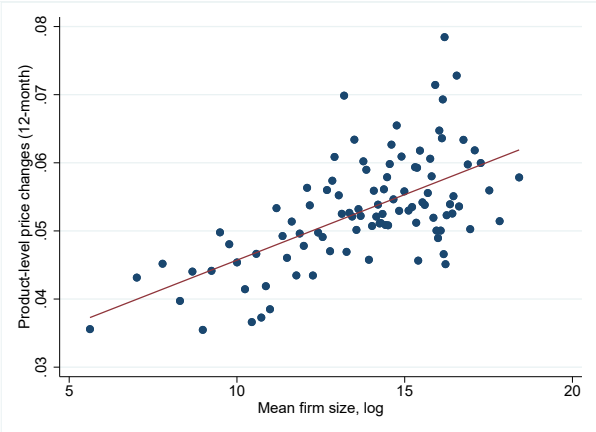

Notes: (A) Distribution of annualized percent change in Prices by Manufacturer/Firm (12 Month Percent Change, averaged by quarter), constructed from median prices, based on 1 percent trimmed micro sample, aggregated to department categories. (Numerator, own calculations) (B) Import shortfalls constructed as mean smoothed percent deviations in the same month compared to 2019 baseline, aggregated to firm-level weighted with firm-level value shares. 12% of firms have an import shortfall of 2 (Census, Panjiva, own calculations)

Panel (A) shows that there is a negative correlation between product-level price growth and the number of countries from which the firm is sourcing, conditional on firm size. Similarly, Panel (B) shows that there is a negative correlation between product-level price growth and the average number of countries from which the firm is sourcing in specific HS codes, conditional on firm size. These raw correlations in the data are suggestive that firms with more diversified supply chain networks potentially experienced lower disruptions and, as a result, lower price hikes.

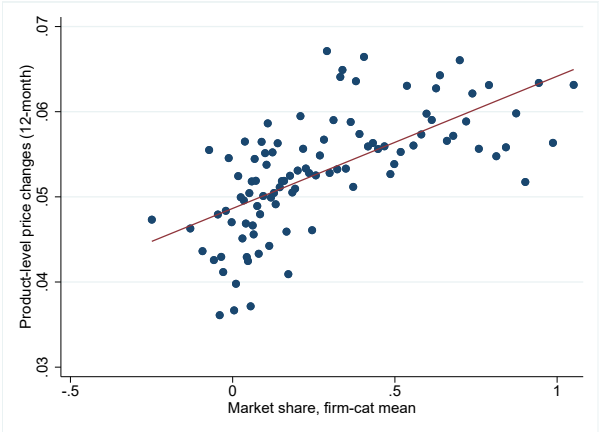
These findings motivate our next step, which is to examine the pass-through of delivery delays and its firm-level heterogeneity using our detailed micro-level data.

**Figure 6.** Price Changes and Firm Size

(A) Product Price Growth vs Firm Size



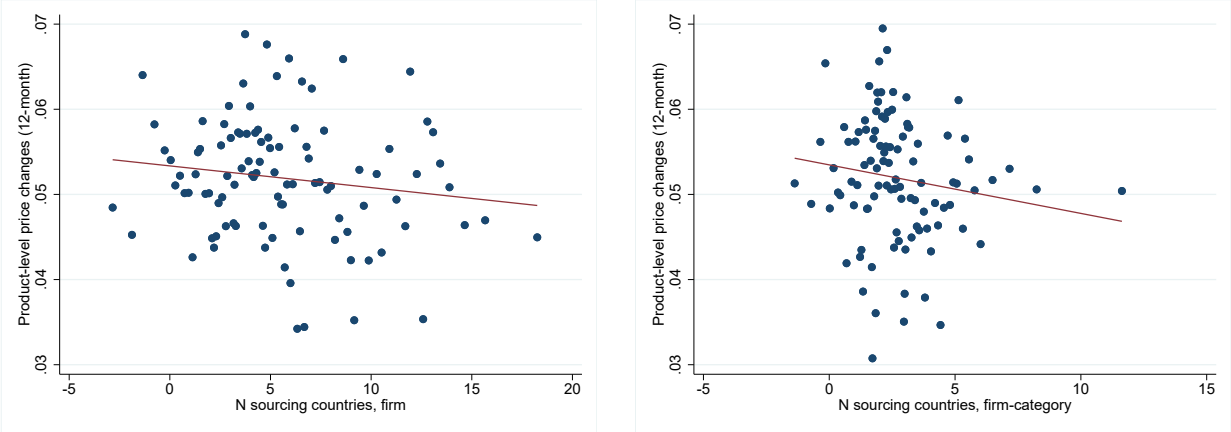

(B) Product Price Growth vs Firm Market Share




*Notes*: (A) Binscatters of product-level price changes against log firm size, defined as the average yearly sales of the firm in Numerator, residualized for year and department fixed effects. (B) Binscatters of product-level price changes against firm market share, defined as the average firm's sales over total sales in the same product category in a year, residualized for year and department fixed effects.

**Figure 7.** Price Changes and Supply Chain Diversification

(A) Product Price Growth vs Supplier Countries (B) Product Price Growth vs Industry-Supplier Countries




*Notes*: (A) Binscatters of product-level price changes against the number of countries the firm is sourcing from, controlling for firm size, residualized for year and department fixed effects. (B) Binscatters of product-level price changes against the number of countries the firm is sourcing from for various HS codes, controlling for firm size, residualized for year and department fixed effects.

## 4.2 Identifying Pass-Through of Delivery Shortfalls to Prices

We begin by exploring the relationship between delivery shortfalls, which serve as proxies for delivery delays due to supply chain disruptions, and consumer price changes using the following OLS specification:

$$\Delta\text{Price}_{p,f,t} = \beta \times \text{Delivery Shortfall}_{f,t(k)} + \gamma \times \Delta MC_{f,t} + \alpha_f + \alpha_{j(p)q(t)} + \epsilon_{p,f,t}, \tag{7}$$

where $p$ denotes a product, $f$ denotes a firm, and $t$ indexes time in months. The variable Delivery Shortfall$_{f,t(k)}$ represents the percent deviation of the $k$-week moving average of imports from their 2019 levels, constructed from BoL data. We do not observe the marginal cost, but we observe a component of the marginal cost that comes from the unit cost of imported products. Hence, we use the foreign-input component of a firm's marginal cost– $\phi \Delta Unit\ Cost_{f,t}$, where $\phi$ is import intensity and $\Delta Unit\ Cost_{f,t}$ is a yearly month-to-month percent change in the HS-code-weighted average of unit import price faced by the firm $f$ at time $t$– as a counterpart of the $\Delta MC_{f,t}$ term. We measure $\phi = 0.125$ based on Census import shares for those industries that correspond to Numerator producers. Firm fixed effects ($\alpha_f$) control for constant firm-specific price changes, while firm category × year-quarter fixed effects ($\alpha_{j(p)q(t)}$) capture common demand or supply factors that vary over time and across product categories.

The primary coefficient of interest, $\beta$, captures the elasticity of price changes with respect to delivery shortfalls, representing the pass-through of supply chain disruptions into consumer prices. The coefficient $\gamma$ is a standard pass-through estimate of marginal cost to prices. Although fixed effects account for aggregate demand factors, OLS estimates of the pass-through elasticities may still be biased due to idiosyncratic demand-side factors. For instance, if a firm faces high consumer demand for a particular

product, it might adjust its import schedule, reducing the observed delivery shortfalls and attenuating the estimated pass-through coefficient $\beta$. To address this potential bias, we require a shift-share instrument that isolates firm-specific shocks driven by external, product-specific increases in delivery times, which are orthogonal to unobserved demand factors. To construct the instrument, we define a firm's exposure to delivery shortfalls as follows:

$$\text{Delivery Shortfall Exposure}_{f,t(k)} \equiv \sum_{h \in S^{HS2}} \text{Delivery Shortfall}_{h,t(k)_{-f}} \times \omega_{h,f,2019},$$

where $h \in S^{HS2}$ represents HS2 product codes, $\text{Delivery Shortfall}_{h,t(k)_{-f}}$ denotes the leave-out mean delivery shortfall in HS code $h$ (excluding firm $f$), and $\omega_{h,f,2019}$ is the pre-determined share of firm $f$'s imports in HS code $h$ as of 2019, before major supply chain disruptions occurred. This exposure measure captures the external component of delivery shortfalls that each firm faces based on its historical import patterns, providing a source of exogenous variation that is uncorrelated with firm-specific demand shocks. In a similar fashion, we construct firm-level marginal cost change exposure as the changes in HS-code-level import unit cost multiplied by the firms' 2019 HS weights:

Using these shift-share exposure measures, we re-estimate the relationship between price changes and delivery disruptions with the following OLS specification:

$$\Delta\text{MC Exposure}_{f,t} \equiv \sum_{h \in S^{HS2}} \phi\, \Delta\text{Unit Cost}_{h,t} \times \omega_{h,f,2019},$$

$$\Delta\text{Price}_{p,f,t} = \beta \times \text{Delivery Shortfall Exposure}_{f,t(k)} + \Delta\text{MC Exposure}_{f,t} + \alpha_f + \alpha_{j(p)q(t)} + \epsilon_{p,f,t}. \quad (8)$$

For our main identification strategy, we employ a shift-share instrumental variable (IV) approach. In the first stage, we regress the observed delivery shortfall, $\text{Delivery Shortfall}_{f,t(k)}$, on the constructed shift-share exposures, $\text{Delivery Shortfall Exposure}_{f,t(k)}$, $\Delta\text{MC Exposure}_{f,t}$, along with the controls specified in Equation (7). This regression provides predicted values of delivery shortfalls, $\widehat{\text{Delivery Shortfall}}_{f,t(k)}$, that isolate the supply-driven component of delivery disruptions while filtering out firm-specific demand influences. Likewise, we also instrument changes in marginal cost- import unit cost. The second stage uses these predicted values in the main IV specification:

$$\Delta\text{Price}_{p,f,t} = \beta \times \widehat{\text{Delivery Shortfall}}_{f,t(k)} + \widehat{\Delta MC_{f,t}} + \alpha_f + \alpha_{j(p)q(t)} + \epsilon_{p,f,t}. \quad (9)$$

This IV strategy leverages exogenous variation from product-specific supply chain disruptions to

overcome challenges to identification. The approach ensures that the estimated elasticity reflects the causal impact of delivery delays rather than confounding factors related to firm-level demand conditions.

## 4.3 Results

We turn to presenting the empirical results of our analysis, focusing on the pass-through of delivery delays to consumer prices. We begin by estimating the baseline pass-through elasticities using OLS and instrumental variable (IV) approaches to identify the causal impact of import shortfalls on price changes. The results provide insights into the magnitude and timing of firms' price adjustments in response to supply chain disruptions. We then examine the heterogeneity in pass-through behavior across firms with different market structures, highlighting how factors such as firm size and market power influence the ability of firms to pass on supply chain-related costs to consumers.

**Baseline Pass-Through Estimates.** We present the baseline estimates of the product-level pass-through of delivery delays to consumer prices. Table 1 reports results from three specifications: standard OLS, OLS using the shift-share exposure variable, and the instrumental variable (IV) approach. Across all specifications, the estimated elasticities of price changes with respect to delivery shortfalls are negative, indicating that increased delivery delays correspond to higher price changes. However, as anticipated, the OLS estimates exhibit a significant downward bias, likely due to unobserved demand-side factors that are not adequately controlled for. The IV estimates in the third column provide a more accurate measure of the causal impact of supply chain disruptions, with the last column indicating a strong instrument (F-statistic = 22) and an implied elasticity of -0.13. Table A.3 in the Appendix shows elasticities in weighted regressions, weighting firms with average firm sales throughout the sample. This significantly increases the coefficient, growing IV elasticity to -0.31.

We explore heterogeneity by product type. Following Argente et al. (2020), we define the durability index for each department in Numerator as the inverse of the frequency of trips the average household makes to purchase products in that department in a year. Table A.2 lists departments with the highest and lowest durability. Using this index, Table A.6 shows that consistent with the narrative, durable products saw significantly higher price growth during the pandemic. However, the pass-through elasticity of delivery delays to prices was relatively low, as evidenced by positive and weakly significant coefficients on the interaction term between shortfalls and the durability index or high-durability dummy.

Table A.4, instead, shows estimates from the firm-level regressions instead of the product-level ones. We see that the elasticities are still negative but lose statistical significance. We then examine if firm-level passthrough elasticity varies at different lags of delivery shortfalls. Table A.5 shows that while

**Table 1.** Pass-Through of Delivery Shortfalls to Prices

| | (1) Price change | (2) Price change | (3) Price change |
|---|---|---|---|
| Shortfall | -0.006*** | | |
| | (0.0016) | | |
| $\Delta MC$ | 0.011*** | | |
| | (0.0032) | | |
| Shortfall, shift-share | | -0.034*** | |
| | | (0.0100) | |
| $\Delta MC$, shift-share | | 0.052*** | |
| | | (0.0153) | |
| Shortfall, IV | | | -0.053*** |
| | | | (0.0173) |
| $\Delta MC$, IV | | | 0.033** |
| | | | (0.0132) |
| Firm FE | Yes | Yes | Yes |
| Cat-Year-Quarter FE | Yes | Yes | Yes |
| R squared | 0.166 | 0.142 | 0.142 |
| Observations | 1489478 | 2217765 | 2217765 |
| I-stage F-stat, q | | | 453.128 |
| I-stage F-stat, p | | | 1502.522 |

Notes: 12-month price changes at the product (firm-brand-category) level on delivery shortfalls (12-week moving average) at the firm level. All variables are in percent change. Column 1 estimates specification (7); column 2 corresponds to (8); column 3 corresponds to estimates from (9). Robust standard errors in parentheses are clustered at the product level.

contemporaneous elasticity is weak, this elasticity sharply grows at longer lags, reaching -0.26 elasticity at a 5-month lag.

To further investigate the timing of firms' responses to import shortfalls, Figure A.5 shows the IV elasticity estimates from Equation (9) across different time horizons of delivery shortfalls (measured in weeks). The results reveal that at shorter horizons, such as the 3-week moving average of imports relative to their 2019 levels, the pass-through to prices is relatively low. However, as the time horizon extends, the magnitude of pass-through increases, suggesting that firms react more strongly to sustained deviations in import schedules. These findings may reflect price rigidities or initial uncertainty about the persistence and severity of the supply chain disruptions, which dampen the immediate price response.[10]

**Firm Heterogeneity.** Our theoretical framework suggests that market structure influences firms' ability to pass on supply chain-related costs to consumers. Specifically, firms with greater market power can more effectively transfer delay shocks into higher consumer prices than smaller firms or those facing more competitive pressures. To empirically verify this hypothesis, we explore the heterogeneity in pass-through behavior across firms with varying market positions.

**Table 2.** Heterogeneity: Pass-Through Elasticity by Firm Size

| | (1) Price change | (2) Price change | (3) Price change |
|---|---|---|---|
| Shortfall (IV) | -0.053*** | 0.365*** | 0.053 |
| | (0.0173) | (0.1331) | (0.0466) |
| $\Delta MC$ (IV) | 0.033** | 0.034** | 0.033** |
| | (0.0132) | (0.0133) | (0.0132) |
| Shortfall (IV) × FirmSize | | -0.023*** | |
| | | (0.0078) | |
| Shortfall (IV) × TopFirm | | | -0.112** |
| | | | (0.0468) |
| Firm FE | Yes | Yes | Yes |
| Cat-Year-Quarter FE | Yes | Yes | Yes |
| R squared | 0.142 | 0.142 | 0.142 |
| Observations | 2217765 | 2217765 | 2217765 |

Notes: IV regressions of price changes at the product (firm-brand-category) level on delivery shortfalls (12-week moving average) at the firm level (equation (9)). Shortfalls and price changes are in percent changes. Column 1 presents the baseline result. Column 2 interacts with the main variable with firm size, defined as the firm's aggregate yearly product sales in Numerator (in logs); column 3 interacts with the main variable with the top firm indicator, defined as a dummy for whether the firm is in the top quintile of sales distribution in its department in a year. All regressions include corresponding levels in the interaction terms (FirmSize, MarketShare, TopFirm). Robust standard errors in parentheses are clustered at the product level.

[10] Figure **??** in Appendix shows similar results, but with stronger coefficients, with weighted regressions.

Table 2 presents results from the IV estimates based on Equation (9), where the main explanatory variable—delivery shortfall exposure—is interacted with firm characteristics such as size (measured by the firm's aggregate yearly product sales, logged), market share (firm sales as a proportion of total sales in the same product category), and top-firm dummy (defined as a dummy for the whether the firm is in the top quintile of sales distribution). The results demonstrate that larger firms and those with greater market shares exhibit significantly higher pass-through estimates, consistent with the notion that market power amplifies a firm's ability to adjust prices in response to supply shocks.

Additionally, in Table 3, we rerun the regressions in different samples, splitting data into high- and low-market share firms based on different cutoffs in columns (2)-(3) and (4)-(5). The results confirm that high-market share firms exhibit much higher passthroughs than smaller firms.

**Table 3.** Heterogeneity: Pass-Through Elasticity for High- and Low- Market Share Firms

| | (1) All | (2) High market share (top quintile) | (3) Low market share (non-top quintile) |
|---|---|---|---|
| Shortfall, IV | -0.053*** | -0.062*** | 0.166 |
| | (0.0173) | (0.0189) | (0.1805) |
| $\Delta MC$, IV | 0.033** | 0.041*** | 0.018 |
| | (0.0132) | (0.0148) | (0.0534) |
| Firm FE | Yes | Yes | Yes |
| Cat-Year-Quarter FE | Yes | Yes | Yes |
| R squared | 0.142 | 0.145 | 0.305 |
| Observations | 2217765 | 1489831 | 723015 |

Notes: IV regressions of price changes at the product (firm-brand-category) level on delivery shortfalls (12-week moving average) at the firm level (equation (9)). Shortfalls and price changes are in percent changes. Columns 2 and 3 split the sample into high- and low- market share firms. Robust standard errors in parentheses are clustered at the product level.

These results underscore the importance of firm heterogeneity in understanding the broader economic implications of supply chain disruptions. Firms with greater market power are better positioned to mitigate the cost pressures associated with delivery delays by passing these costs on to consumers, exacerbating inflationary pressures in markets where such firms dominate. The heterogeneity in pass-through responses emphasizes the need to account for market structure when assessing the impact of supply chain disruptions on consumer prices.

# 5 Quantification

tbd.

# 6 Conclusion

tbd

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# A Additional Derivations

This appendix section provides additional derivations for the results in Section 2.

## A.1 Proofs for Propositions

**Proof for Proposition 1** Consider the profit maximization problem of firm $i$ written in the conjectural variation form, where the firm chooses both its log price $p_i$ and its log stock–in shifter $\tau_i$. The problem is given by

$$\begin{aligned}\max_{p_i,\tau_i,\boldsymbol{p}_{-i},\boldsymbol{\tau}_{-i}} \quad & \Big\{\exp\Big\{p_i + q_i\big(p_i,\boldsymbol{p}_{-i},\tau_i,\boldsymbol{\tau}_{-i};\xi\big) + s_i\big(q_i,\tau_i\big)\Big\} \\ & \qquad - TC_i\Big(\exp\big\{q_i\big(p_i,\boldsymbol{p}_{-i},\tau_i,\boldsymbol{\tau}_{-i};\xi\big)\big\},\tau_i\Big)\Big\} \\ \text{subject to} \quad & h_{-i}\big(p_i,\tau_i,\boldsymbol{p}_{-i},\boldsymbol{\tau}_{-i};\xi\big) = 0.\end{aligned}$$

Here, $p_i$ and $q_i$ are the log price and log quantity demanded of firm $i$; $s_i(q_i,\tau_i)$ is a function that shifts the effective stock–in probability (so that higher $s_i$ implies improved product availability); $TC_i(\cdot,\tau_i)$ is the total cost function (in levels); and $h_{-i}(\cdot)$ is the conjectural variation vector function with elements $h_{ij}(\cdot)$ for $j \neq i$. (For brevity we omit the time subscript $t$.)

This formulation nests models of monopolistic competition, oligopolistic Bertrand competition, and oligopolistic Cournot competition, provided that the demand system is invertible. In particular, to capture firm behavior under monopolistic and oligopolistic Bertrand competition we may choose the conjectural variation function as

$$h_{-i}\big(p_i,\tau_i,\boldsymbol{p}_{-i},\boldsymbol{\tau}_{-i};\xi\big) = \begin{cases}\boldsymbol{p}_{-i} - \boldsymbol{p}^*_{-i}, \\ \boldsymbol{\tau}_{-i} - \boldsymbol{\tau}^*_{-i},\end{cases}$$

which corresponds to the assumption that firm $i$ believes its choices do not affect its competitors' prices (set at $\boldsymbol{p}^*_{-i}$) or stock–in shifters (set at $\boldsymbol{\tau}^*_{-i}$). The case of Cournot competition requires choosing $h_{-i}(\cdot)$ so that it implies $\boldsymbol{q}_{-i} \equiv \boldsymbol{q}^*_{-i}$ for some given $\boldsymbol{q}^*_{-i}$; with an invertible demand system, this can be ensured by setting

$$h_{-i}\big(p_i,\tau_i,\boldsymbol{p}_{-i},\boldsymbol{\tau}_{-i};\xi\big) = -\Big(\boldsymbol{q}_{-i}\big(p_i,\boldsymbol{p}_{-i},\tau_i,\boldsymbol{\tau}_{-i};\xi\big) - \boldsymbol{q}^*_{-i}\Big).$$

Thus, the firm's behavior under competition in both prices and product availability is captured by a conditional profit maximization problem.

We introduce the following notation:

1. $e^{p_i+q_i}\lambda_{ij}$ for $j \neq i$ denotes the Lagrange multipliers associated with the constraints in the maximization problem.
2. $\zeta_{ijk}(\boldsymbol{p},\xi) \equiv \partial h_{ij}(\boldsymbol{p},\xi)/\partial p_k$ is the elasticity of the conjectural variation function with respect to $p_k$, with $\zeta_{ijj}(\cdot) > 0$ as a normalization; the matrix $Z_i \equiv \{\zeta_{ijk}(\cdot)\}_{j,k\neq i}$ is assumed to have full rank. Similarly, we define

   $$\theta_{ijk}(\boldsymbol{p},\xi) \equiv \frac{\partial h_{ij}(\boldsymbol{p},\xi)}{\partial \tau_k},$$

   and denote by $\Theta_i \equiv \{\theta_{ijk}(\cdot)\}_{j,k\neq i}$ the corresponding matrix of cross–stock–in elasticities.
3. The own–price elasticity of demand is

   $$\epsilon_i(\boldsymbol{p},\xi) \equiv -\frac{\partial q_i(\boldsymbol{p},\xi)}{\partial p_i} > 0,$$

   and the cross–price elasticities are given by

   $$\delta_{ij}(\boldsymbol{p},\xi) \equiv \frac{\partial q_i(\boldsymbol{p},\xi)}{\partial p_j} \quad (j \neq i).$$

4. Similarly, define the effective own–stock–in elasticity as

   $$\eta_i(\boldsymbol{p},\tau,\xi) \equiv \frac{\partial\big(q_i + s_i\big)}{\partial \tau_i} > 0,$$

and the cross–stock–in elasticities as

$$\gamma_{ij}(\boldsymbol{p},\tau,\xi) \equiv \frac{\partial\big(q_i + s_i\big)}{\partial \tau_j} \quad (j \neq i).$$

The first–order conditions (after simplification) for the profit maximization problem with respect to $p_i$ are then given by

$$\Big(1 - \epsilon_i + \epsilon_i\, e^{-\mu_i}\Big) + \sum_{k\neq i} \lambda_{ik}\, \zeta_{iki} = 0,$$

$$\forall\, j \neq i \quad \Big(-\delta_{ij} + \delta_{ij}\, e^{-\mu_i}\Big) + \sum_{k\neq i} \lambda_{ik}\, \zeta_{ikj} = 0,$$

where the log markup is defined by $\mu_i \equiv p_i - mc_i$, with $mc_i \equiv \ln\Big(\partial TC_i/\partial Q_i\Big)$ being the log marginal cost. In the presence of the stock–in shifter, the effective demand depends on both $q_i$ and $s_i$; consequently, the perceived elasticity of demand is modified and given by

$$\sigma_i \equiv \epsilon_i(1+\kappa_i) - \zeta_i' Z_i^{-1}\delta_i - \theta_i' \Theta_i^{-1}\gamma_i,$$

where $\kappa_i \equiv \partial s_i/\partial q_i$, and $\zeta_i \equiv \{\zeta_{iji}\}_{j\neq i}$ and $\delta_i \equiv \{\delta_{ij}\}_{j\neq i}$ are $(N-1)\times 1$ vectors. The matrix $Z_i \equiv \{\zeta_{ijk}\}_{j\neq i,k\neq i}$ has full rank by the invertibility assumption, and similarly for the stock–in part with $\theta_i \equiv \{\theta_{iji}\}_{j\neq i}$ and $\gamma_i \equiv \{\gamma_{ij}\}_{j\neq i}$ and the matrix $\Theta_i \equiv \{\theta_{ijk}\}_{j\neq i,k\neq i}$.

Solving the first–order conditions yields the expression for the optimal markup of firm $i$:

$$\mu_i = \ln \frac{\sigma_i}{\sigma_i - 1}.$$

Since $\epsilon_i$, $\zeta_{ijk}$, and $\delta_{ij}$ are functions of $(\boldsymbol{p},\xi)$ (and now also of $\tau$ through $s_i$), it follows that $\sigma_i \equiv \sigma_i(\boldsymbol{p},\tau;\xi)$. Therefore, we define the log markup function as

$$\mathscr{M}_i(\boldsymbol{p},\tau;\xi) \equiv \ln \frac{\sigma_i(\boldsymbol{p},\tau;\xi)}{\sigma_i(\boldsymbol{p},\tau;\xi) - 1}.$$

Thus, the optimal price of firm $i$ solves the fixed point equation

$$\tilde{p}_i = mc_i + \mathscr{M}_i\big(\tilde{p}_i, \tilde{\tau}_i, \boldsymbol{p}_{-i}, \boldsymbol{\tau}_{-i}; \xi\big).$$

An analogous argument, based on the first–order condition with respect to the stock–in shifter $\tau_i$, leads to a similar fixed point characterization for the optimal stock–in decision. Defining the effective stock–in elasticity as

$$\phi_i \equiv \eta_i - \zeta_i^{\tau\prime} Z_i^{-1}\delta_i^{\tau} - \theta_i^{\tau\prime}\Theta_i^{-1}\gamma_i,$$

where $\eta_i \equiv \partial(q_i + s_i)/\partial\tau_i$ is the own elasticity with respect to $\tau_i$ and $\delta_i^{\tau} \equiv \{\partial q_i/\partial\tau_j\}_{j\neq i}$, and where $\zeta_i^{\tau}$ and $\theta_i^{\tau}$ are the corresponding derivatives of the conjectural variation function with respect to $\tau_i$, we define the stock–in premium function by

$$\mathscr{T}_i(p_i,\tau_i,\boldsymbol{p}_{-i},\boldsymbol{\tau}_{-i};\xi) \equiv -\ln\Big(1 - \frac{mc_i^{\tau}}{\phi_i}\Big),$$

with $mc_i^{\tau}$ the log marginal cost of adjusting the stock–in shifter. Hence, the optimal stock–in shifter satisfies the fixed point equation

$$\tilde{\tau}_i = mc_i^{\tau} + \mathscr{T}_i\big(\tilde{p}_i, \tilde{\tau}_i, \boldsymbol{p}_{-i}, \boldsymbol{\tau}_{-i}; \xi\big).$$

This completes the proof of Proposition 1 (Extended). Notice that when the stock–in shifter is absent (or when $s_i(\cdot)$ is constant), the above derivation reduces to the standard framework in which only price is chosen. In our extended model, the generalized elasticities $\sigma_i$ and $\phi_i$ capture both the direct demand sensitivities and the strategic interdependencies across firms in the dimensions of price and product availability.

**Proof for Proposition 2** Assume that product availability enters the expenditure function via a stock–in adjustment factor. In particular, let the log aggregate expenditure be given by

$$z_t = \ln \min_{\{Q_{it}\}} \left\{ \sum_{i=1}^{N} P_{it} Q_{it}\, s_{it}(\tau_{it}) \,\middle|\, U\big(\{Q_{it}\}; Q_t\big) = 1 \right\}.$$

Here, $s_{it}(\tau_{it})$ adjusts the effective expenditure for product $i$ based on its stock–in probability (or availability), with $\tau_{it}$ being the firm's stock–in shifter.

Let $E(s)$ denote the minimized expenditure:

$$E(s) = \min_{\{Q_{it}\}} \left\{ \sum_{i=1}^{N} P_{it} Q_{it} s_{it}(\tau_{it}) \mid U(\{Q_{it}\}; Q_t) = 1 \right\}$$

so that $z_t = \ln E(s)$. At the optimum, let $Q_{it}^*$ be the optimal quantity for firm $i$. Define the Lagrangian for the cost minimization problem as

$$L(\{Q_{it}\}, \lambda; s) = \sum_{i=1}^{N} P_{it} Q_{it} s_{it}(\tau_{it}) - \lambda (U(\{Q_{it}\}; Q_t) - 1)$$

By the Envelope Theorem, the derivative of the minimized expenditure $E(s)$ with respect to $s_{it}$ is given by the direct partial derivative evaluated at the optimum, i.e.,

$$\frac{\partial E(s)}{\partial s_{it}} = \left. \frac{\partial L}{\partial s_{it}} \right|_{Q_{it}=Q_{it}^*} = P_{it} Q_{it}^*$$

(Any indirect effects via the optimal $Q_{it}^*$ vanish because the first-order conditions for $Q_{it}$ ensure that $\partial L / \partial Q_{it} = 0$.) Taking the derivative of $z_t = \ln E(s)$ with respect to $s_{it}$, we obtain

$$\frac{\partial z_t}{\partial s_{it}} = \frac{1}{E(s)} \cdot \frac{\partial E(s)}{\partial s_{it}} = \frac{P_{it} Q_{it}^*}{\sum_{k=1}^{N} P_{kt} Q_{kt}^*}$$

In summary, by the Envelope Theorem applied to this cost minimization problem, differentiating $z_t$ with respect to $s_{it}$ gives

$$\frac{\partial z_t}{\partial s_{it}} = \frac{P_{it} Q_{it}^*}{\sum_{k=1}^{N} P_{kt} Q_{kt}^*} \equiv S_{it},$$

where $Q_{it}^*$ is the optimal quantity for firm $i$ and $S_{it}$ is its expenditure (or revenue) market share. Now, if the availability adjustment is given by a function $s_{it} = s(\tau_{it})$, then by the chain rule we have

$$\frac{\partial z_t}{\partial \tau_{it}} = \frac{\partial z_t}{\partial s_{it}} \cdot \frac{\partial s(\tau_{it})}{\partial \tau_{it}} = S_{it} \frac{\partial s(\tau_{it})}{\partial \tau_{it}}.$$

Next, suppose the markup function for firm $i$ depends on competitors' stock–in shifters only through an aggregate availability index, so that we can write

$$\mathcal{M}_i(p_t, \tau_t; \xi_t) = \tilde{\mathcal{M}}_i\Big(p_t, z\big(s(\tau_t)\big); \xi_t\Big).$$

Then, by the chain rule the partial derivative of the markup function with respect to a competitor $j$'s stock–in shifter is

$$\frac{\partial \mathcal{M}_i}{\partial \tau_j} = \frac{\partial \tilde{\mathcal{M}}_i}{\partial z} \cdot \frac{\partial z}{\partial s(\tau)} \cdot \frac{\partial s(\tau)}{\partial \tau_j}.$$

By the Envelope condition we have already shown that

$$\frac{\partial z}{\partial s(\tau)} \cdot \frac{\partial s(\tau)}{\partial \tau_j} = S_{jt}.$$

Hence, it follows that

$$\frac{\partial \mathcal{M}_i}{\partial \tau_j} = \frac{\partial \tilde{\mathcal{M}}_i}{\partial z} S_{jt}.$$

When constructing the competitor delay index, we define the weight on competitor $j$ as

$$\omega^{\tau}_{ijt} \equiv \frac{\frac{\partial \mathcal{M}_i}{\partial \tau_j}}{\sum_{k\neq i}\frac{\partial \mathcal{M}_i}{\partial \tau_k}} = \frac{\frac{\partial \tilde{\mathcal{M}}_i}{\partial z} S_{jt}}{\frac{\partial \tilde{\mathcal{M}}_i}{\partial z}\sum_{k\neq i} S_{kt}} = \frac{S_{jt}}{1-S_{it}},$$

since the market shares of competitors sum to $1-S_{it}$. Consequently, the competitor delay index is given by

$$d\tau_{-it} \equiv \sum_{j\neq i} \omega^{\tau}_{ijt}\, d\tau_{jt} = \sum_{j\neq i} \frac{S_{jt}}{1-S_{it}}\, d\tau_{jt}\,.$$

This completes the proof: by explicitly incorporating product availability via the function $s(\tau_{it})$ into the aggregate expenditure function, we derive—using the Envelope condition—that the marginal effect of a competitor's stock–in shifter on the markup function is proportional to its market share. Therefore, the competitor delay index aggregates individual delay changes with weights $\omega^{\tau}_{ijt} = S_{jt}/(1-S_{it})$, analogous to the competitor price index in the original framework.

**Proof of Proposition 3** In the frictionless inventory–pricing problem, the firm simultaneously chooses an inventory level $Q$ and a price $p$ to maximize instantaneous profits given by

$$\pi(Q,p) = s(Q,q(p))(p-c)q(p) - Qc_h,$$

where $c$ is the procurement cost, $c_h$ is the holding cost, $q(p) = Ap^{-\eta}$ is an iso-elastic demand function, and $s(Q,p)$ is the "stock-in" function (assumed iso-elastic)- denoting the fraction of demand served. By defining the stock-in elasticity with respect to price as

$$\varepsilon_s \equiv \frac{\partial s(Q,p)}{\partial p}\frac{p}{s(Q,p)},$$

$$\varepsilon_s \equiv \left(\frac{\partial s(Q,q(p))}{\partial q}\frac{q}{s(Q,p)}\right)\left(\frac{\partial q(p)}{\partial p}\frac{p}{q}\right) = \kappa \times \eta,$$

where $\kappa \equiv \frac{d\ln s}{d\ln q}$ and the first-order condition for pricing yields the optimal price:

$$p^* = \frac{\varepsilon_s - \eta}{\varepsilon_s - \eta + 1}\, c.$$

$$p^* = \frac{\kappa\eta - \eta}{\kappa\eta - \eta + 1}\, c.$$

$$p^* = \frac{(1-\kappa)\eta}{(1-\kappa)\eta + 1}\, c.$$

$$p^* = \frac{(\kappa-1)\eta}{(\kappa-1)\eta - 1}\, c.$$

Similarly, introducing the stock-in elasticity with respect to inventory, $\varepsilon_{s,Q}$, the first-order condition with respect to $Q$ leads to an optimal inventory level given by

$$Q^* = \frac{\varepsilon_{s,Q}\, s(Q^*,p^*)(p^*-c)\, q(p^*)}{c_h}.$$

To assess the sensitivity of profits to deviations from the optimal inventory, a **second-order Taylor expansion** of the profit function around $Q^*$ is performed. This yields an approximate per-period loss function:

$$L(Q) \approx \frac{1}{2}\gamma\, \varepsilon_s\, (\varepsilon_s - 1)(Q-Q^*)^2\, Q^{\varepsilon_s - 2},$$

where the iso-elastic stock-in function is assumed to take the form $s(Q,p) = \gamma Q^{\varepsilon_s}$. This quadratic approximation captures the cost of deviating from the optimal inventory level.

[solve for optimal Q*??]

Transition from static to dynamic model. Take p from the previous model.. Take Q from the previous model- not sure....??

Moving to a **dynamic setting with stochastic demand and delays**, the model introduces a fixed observation (or adjustment) cost $\phi$ to observe the state of the inventory, along with stochastic demand characterized by drift ($\pi$) and

variance ($\sigma^2$). Additionally, the possibility of delivery delays is captured via a delay probability $q$ and a delay length $\Delta$. In this framework, the firm chooses a review time interval $\tau$- a period between two successive observation (adjustment) dates, minimizing the expected present value of observation (adjustment) costs over an infinite horizon. [prices constant as above] The recursive value function is formulated as

$$V = \min_{\tau}\left[\phi + B\pi^2 v(\tau) + qB\int_0^{\tau+\Delta} e^{-\rho t} t\sigma^2 dt + (1-q)B\int_0^{\tau} e^{-\rho t} t\sigma^2 dt + qe^{-\rho(\tau+\Delta)}V + (1-q)e^{-\rho\tau}V\right],$$

where $v(\tau)$ results from optimally managing the price deviation during the interval $\tau$. In the special case of no drift ($\pi = 0$) and low discounting ($\rho \to 0$), the optimal interval between observations (or adjustments) simplifies to

$$\tau^* = \sqrt{\frac{2\phi}{B\sigma^2}} - q\Delta.$$

This result indicates that higher fixed costs $\phi$ lead to longer intervals between adjustments, whereas greater demand variability $\sigma^2$ and more pronounced delays (through larger $q$ or $\Delta$) necessitate more frequent adjustments. When a positive drift ($\pi > 0$) is present, the optimal interval adjusts to

$$\tau^* = \sqrt{\frac{2\phi}{B\sigma^2} - \frac{q\Delta\,\pi^2}{\sigma^2}} - q\Delta,$$

showing that higher drift rates require even more frequent inventory reviews.

Overall, these derivations integrate static inventory and pricing choices with dynamic, stochastic adjustment policies, providing clear insights into how fixed costs, demand variability, drift, and delay factors jointly determine optimal inventory and adjustment strategies.

In the parametric model, the firm faces iso-elastic demand given by $q(p) = Ap^{-\eta}$, where $\eta$ represents the inherent price sensitivity. However, the firm's ability to serve demand is also affected by product availability, captured by a stock–in function $s(Q,p)$ whose responsiveness is measured by $\varepsilon_s$. The optimal pricing rule derived from the model can be written in markup form as $\frac{p^*}{c} = \frac{\sigma}{\sigma-1}$, and equating this with the expression obtained from the joint choice yields the correspondence $\sigma = \varepsilon_s - \eta + 1$. This identification shows that the effective, or perceived, demand elasticity in the nonparametric framework is an aggregate measure that blends the direct elasticity of demand with the impact of product availability.

In the parametric model, the replenishment cycle is determined by the firm's review interval $\tau$ and any additional probabilistic delivery delays characterized by a delay probability $q$ and delay duration $\Delta$. The total effective cycle time is then given by $\tau + q\Delta$. Meanwhile, the time it takes for the firm to run down its available inventory is captured by the first-hitting time $\tau_Q$, where, under a consumption (or drift) rate $\pi$, the expected run-down time is $\mathbb{E}[\tau_Q] = \frac{Q}{\pi}$.

This setup naturally leads to a definition of the stock–in function in terms of time: the fraction of the cycle during which the firm is stocked is given by

$$s = \frac{\tau_Q}{\tau + q\Delta} \approx \frac{Q/\pi}{\tau + q\Delta}.$$

In other words, the likelihood that the firm is in stock (and able to serve demand) depends positively on the inventory level $Q$ relative to the consumption rate $\pi$ and negatively on the length of the replenishment cycle $\tau + q\Delta$. This formulation ties together the dynamic ordering policy (through the review time and delay) and the inventory level decision, paralleling how the stock–in function in the nonparametric model shifts effective demand by affecting the availability of the product.

**Proof of Proposition 4** We assume that ideas (or technologies) are generated by a Poisson process on $(0,\infty)$ with a general cumulative intensity measure $\Lambda(z)$ (i.e. the expected number of ideas with productivity at least $z$). A common specification is to take $\Lambda(z) = T z^{-\theta}$, though here we maintain a general form. Each idea with productivity $z$ yields a delivered cost

$$C = \frac{w\,d}{z},$$

so that higher productivity implies lower cost.

**Distribution of the First Best.** The probability that no idea has productivity exceeding $z$ is

$$\Pr\{Z_{(1)} < z\} = \exp\{-\Lambda(z)\}.$$

Thus, the cumulative distribution function (CDF) of the maximum (first best) is

$$F(z) = \exp\{-\Lambda(z)\}.$$

**Joint Distribution of the First and Second Best.** Let $Z_{(1)}$ and $Z_{(2)}$ denote the highest and second highest productivities, respectively. Standard extreme–value theory yields the joint CDF

$$F(z_1, z_2) = \Pr\{Z_{(1)} \le z_1,\ Z_{(2)} \le z_2\} = \exp\{-\Lambda(z_2)\}\Big[1 + \Lambda(z_2) - \Lambda(z_1)\Big], \quad z_1 \ge z_2.$$

Differentiating with respect to $z_1$ and $z_2$ gives the joint density

$$f(z_1, z_2) = \lambda(z_1)\,\lambda(z_2)\,\exp\{-\Lambda(z_2)\}, \quad z_1 \ge z_2,$$

where $\lambda(z) = \frac{d\Lambda(z)}{dz}$. Consequently, the marginal density of the second best is

$$g(z) = \lambda(z)\,\Lambda(z)\,\exp\{-\Lambda(z)\}.$$

**Markup Distribution.** Since cost is inversely related to productivity, the delivered cost is given by $C = \frac{w\,d}{z}$. Thus, if $Z_{(1)}$ is the highest productivity (yielding the lowest cost) and $Z_{(2)}$ is the second highest, the *raw markup* is

$$M = \frac{C_{(2)}}{C_{(1)}} = \frac{w\,d/Z_{(2)}}{w\,d/Z_{(1)}} = \frac{Z_{(1)}}{Z_{(2)}}.$$

Noting that the event $\{M \le m\}$ is equivalent to $\{Z_{(1)} \le m\,Z_{(2)}\}$, the conditional CDF of $Z_{(1)}$ given $Z_{(2)} = z$ is

$$\Pr\{Z_{(1)} \le m\,z \mid Z_{(2)} = z\} = 1 - \frac{\Lambda(mz)}{\Lambda(z)}.$$

Averaging over $Z_{(2)}$ with density $g(z)$ yields the unconditional markup distribution:

$$\Pr(M \le m) = \int_0^\infty \left[1 - \frac{\Lambda(mz)}{\Lambda(z)}\right] g(z)\,dz = \int_0^\infty \left[1 - \frac{\Lambda(mz)}{\Lambda(z)}\right] \lambda(z)\,\Lambda(z)\,\exp\{-\Lambda(z)\}\,dz.$$

In the special case $\Lambda(z) = T\,z^{-\theta}$ we have $\Lambda(mz) = m^{-\theta}\Lambda(z)$, so that

$$\Pr(M \le m) = 1 - m^{-\theta}, \quad m \ge 1.$$

We now consider a modification. In a special case we set

$$\Lambda(z) = T z^{-\theta} e^{-z}$$

which introduces an exponential damping into the intensity measure. In this case,

$$\Lambda(mz) = T(mz)^{-\theta} e^{-mz} = m^{-\theta}\,T z^{-\theta} e^{-mz}$$

so that

$$\frac{\Lambda(mz)}{\Lambda(z)} = m^{-\theta} e^{-z(m-1)}$$

Thus, the markup CDF becomes

$$\Pr(M \le m) = \int_0^\infty \left[1 - m^{-\theta} e^{-z(m-1)}\right] \lambda(z)\Lambda(z)\exp\{-\Lambda(z)\}dz$$

A saddle-point (or Laplace) approximation suggests that the dominant contribution to this integral comes from values of $z$ around an effective value $z^*$.[1] In that case we may approximate the markup distribution by

[1] To determine an effective value $z^*$ that dominates the Laplace (saddle–point) approximation of an integral, one typically

$$\Pr(M \le m) \approx 1 - m^{-\theta} e^{-z^*(m-1)}$$

Thus, the markup CDF becomes

$$\Pr(M \le m) = \int_0^\infty \left[1 - m^{-\theta} e^{-z(m-1)}\right] \lambda(z)\Lambda(z) \exp\{-\Lambda(z)\} dz$$

A saddle-point (or Laplace) approximation suggests that the dominant contribution to this integral comes from values of $z$ around an effective value $z^*$. In that case we may approximate the markup distribution by

$$\Pr(M \le m) \approx 1 - m^{-\theta} e^{-z^*(m-1)}$$

Thus, for $m$ close to 1 the distribution is nearly linear in $(m-1)$, while in the tail the additional exponential factor leads to a faster decay than the pure Pareto law. In other words, the exponential term in $\Lambda(z)$ steepens the tail relative to the standard case.

**Sourcing (Expenditure) Shares.** Consider a multi–country setting where country $i$ has its own intensity measure $\Lambda_i(z)$ and delivers goods to destination $n$ at cost

$$C_{ni} = \frac{w_i\, d_{ni}}{z}.$$

For a given country $i$, the probability that its delivered cost is below $c$ is

$$G_{ni}(c) = 1 - \exp\Big\{-\Lambda_i\Big(\frac{w_i\, d_{ni}}{c}\Big)\Big\}.$$

Because the processes across countries are independent, the probability that no country other than $i$ can deliver at cost below $c$ is

$$\prod_{j \ne i} \exp\Big\{-\Lambda_j\Big(\frac{w_j\, d_{nj}}{c}\Big)\Big\}.$$

Thus, the density that country $i$ supplies the good at cost $c$ is

$$g_{ni}(c) = \frac{d}{dc}\Big[1 - \exp\Big\{-\Lambda_i\Big(\frac{w_i\, d_{ni}}{c}\Big)\Big\}\Big] \prod_{j \ne i} \exp\Big\{-\Lambda_j\Big(\frac{w_j\, d_{nj}}{c}\Big)\Big\}.$$

Then the sourcing share for country $i$ is given in general by

$$\pi_{ni} = \int_0^\infty g_{ni}(c)\, dc.$$

In the standard Eaton–Kortum case where $\Lambda_i(z) = T_i\, z^{-\theta}$, one may show (after appropriate changes of variables) that

$$\pi_{ni} = \frac{T_i\, (w_i\, d_{ni})^{-\theta}}{\sum_j T_j\, (w_j\, d_{nj})^{-\theta}}.$$

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defines a function $\phi(z) = \ln f(z) - \Lambda(z)$, where $f(z)$ is the non-exponential part of the integrand. The saddle–point is then obtained by solving

$$\phi'(z^*) = 0.$$

In our context—e.g. when approximating the markup distribution—the integrand is dominated by the marginal density of the second–best, $g(z) = \lambda(z)\,\Lambda(z)\, e^{-\Lambda(z)}$. One may choose $z^*$ as the mode of $g(z)$, determined by solving

$$\frac{d}{dz}\Big[\ln \lambda(z) + \ln \Lambda(z) - \Lambda(z)\Big]\Big|_{z=z^*} = 0.$$

For the special case

$$\Lambda(z) = T\, z^{-\theta} e^{-z},$$

this condition typically leads to a transcendental equation that does not admit a closed–form solution; hence, $z^*$ must be determined numerically or via asymptotic approximations.

In the Eaton–Kortum model, each country $i$ generates ideas according to a Poisson process with cumulative intensity

$$\Lambda(z) = T\, z^{-\theta} e^{-z}.$$

A firm with productivity $z$ produces at delivered cost

$$C = \frac{w\, d}{z}.$$

Thus, the probability that country $i$ can deliver at cost below $c$ is

$$G_{ni}(c) = 1 - \exp\left\{-\Lambda_i\Big(\frac{w_i\, d_{ni}}{c}\Big)\right\} = 1 - \exp\left\{-T_i\Big(\frac{w_i\, d_{ni}}{c}\Big)^{-\theta} e^{-\frac{w_i\, d_{ni}}{c}}\right\}.$$

For destination $n$, the sourcing (trade) share for country $i$ is given generally by

$$\pi_{ni} = \int_0^\infty \frac{d}{dc}\left[1 - \exp\left\{-\Lambda_i\Big(\frac{w_i\, d_{ni}}{c}\Big)\right\}\right] \prod_{j\neq i} \exp\left\{-\Lambda_j\Big(\frac{w_j\, d_{nj}}{c}\Big)\right\} dc\,.$$

A change of variable (e.g. $x = w_i\, d_{ni}/c$) leads to an integral representation that, in general, does not simplify to an elementary closed form. However, if the integral is dominated by values near a saddle–point $c^*$ (or equivalently $x^*$), then a Laplace approximation yields an approximate closed–form expression. In particular, one obtains

$$\pi_{ni} \approx \frac{T_i\,(w_i\, d_{ni})^{-\theta} e^{-w_i\, d_{ni}/c^*}}{\sum_j T_j\,(w_j\, d_{nj})^{-\theta} e^{-w_j\, d_{nj}/c^*}},$$

where the effective threshold $c^*$ is determined by solving the saddle–point equation for the dominant contribution in the integrand. In the limit where the exponential damping is weak (so that $e^{-w_i\, d_{ni}/c^*} \approx 1$), the expression recovers the standard result:

$$\pi_{ni} \approx \frac{T_i\,(w_i\, d_{ni})^{-\theta}}{\sum_j T_j\,(w_j\, d_{nj})^{-\theta}}.$$

Thus, while the full closed–form expression under $\Lambda(z) = T\, z^{-\theta} e^{-z}$ is not elementary, a saddle–point approximation yields an approximate formula that incorporates an extra exponential damping factor in the trade shares.

**Summary of Key Results:**

- The first best has CDF
$$F(z) = \exp\{-\Lambda(z)\}.$$
- The joint distribution of the first and second best is
$$F(z_1, z_2) = \exp\{-\Lambda(z_2)\}\Big[1 + \Lambda(z_2) - \Lambda(z_1)\Big], \quad z_1 \geq z_2,$$
with joint density
$$f(z_1, z_2) = \lambda(z_1)\,\lambda(z_2)\,\exp\{-\Lambda(z_2)\}.$$
- The markup (competitive margin) defined as
$$M = \frac{Z_{(1)}}{Z_{(2)}},$$
has distribution
$$\Pr(M \leq m) = \int_0^\infty \Big[1 - \frac{\Lambda(mz)}{\Lambda(z)}\Big]\lambda(z)\,\Lambda(z)\,\exp\{-\Lambda(z)\}\,dz.$$
In the case $\Lambda(z) = T\, z^{-\theta}$ this simplifies to
$$\Pr(M \leq m) = 1 - m^{-\theta}, \quad m \geq 1.$$

- The sourcing share for country $i$ is given by the integral

$$\pi_{ni} = \int_0^\infty \left[ -\frac{d}{dc} \exp\left\{ -\Lambda_i\left( \frac{w_i\, d_{ni}}{c} \right) \right\} \right] \prod_{j \neq i} \exp\left\{ -\Lambda_j\left( \frac{w_j\, d_{nj}}{c} \right) \right\} dc,$$

  which, in the special case $\Lambda_i(z) = T_i\, z^{-\theta}$, reduces to the familiar expression

$$\pi_{ni} = \frac{T_i\, (w_i\, d_{ni})^{-\theta}}{\sum_j T_j\, (w_j\, d_{nj})^{-\theta}}.$$

**Mapping against Non-parametric model** We assume that the relevant competitor price is given by

$$p^*_{-i} = \mathbb{E}\Big[ \min_{j \neq i} \{ p_j - s_i(\tau_{it}) \} \Big],$$

so that firm $i$ perceives its competition in terms of the minimum posted price among rivals, adjusted by its own stock–in function $s_i(\tau_{it})$. This adjustment implies that a higher stock–in probability for firm $i$ (i.e. a larger $s_i(\tau_{it})$) effectively raises the competitor's price from firm $i$'s perspective, as consumers are more likely to purchase from $i$ when it is readily available. In other words, firm $i$'s own availability mitigates the intensity of competitive pressure by "discounting" the effective competitive price, thereby altering the competitive landscape that the firm faces.

In this setting, the conjectural variation function must be adjusted to account for the fact that the best competitor price is now endogenous and depends on $s_i$. We write the constraint as

$$h_{-i}(p_i, \tau_i, \boldsymbol{p}_{-i}, \boldsymbol{\tau}_{-i}) = \boldsymbol{p}_{-i} - p^*_{-i},$$

with the cross–elasticities defined by

$$\zeta_{ijk} \equiv \frac{\partial h_{ij}}{\partial p_k}.$$

These cross–elasticities capture not only the direct effect of a rival's price change on the competitive environment but also how that effect is modulated by the firm's own stock–in probability through $s_i(\tau_{it})$. Consequently, the perceived demand elasticity, given by

$$\sigma_i = \epsilon_i(1 + \kappa_i) - \zeta_i' Z_i^{-1} \delta_i - \theta_i' \Theta_i^{-1} \gamma_i,$$

can be interpreted as follows: the term $\epsilon_i(1 + \kappa_i)$ reflects the baseline responsiveness of demand to changes in firm $i$'s price and availability, while the subtracted cross–elasticity terms account for the strategic feedback effects—namely, how changes in competitors' prices (and their implied availability) influence the effective best competitor price. In this manner, a higher stock–in elasticity (i.e. a stronger influence of $s_i(\tau_{it})$) reduces the competitive pressure from rivals, leading to a higher perceived elasticity $\sigma_i$ and thus lower optimal markups.

# B Data Appendix

## B.1 Numerator Data

Our baseline sample excludes the items[2] whose Numerator sector is either "Limited Service Restaurant," "Restaurant," "Non-Item," "Unknown," or "Indeterminate Category." In addition, we restrict the sample to the items for which we have non-missing brand or manufacturer information and at least one non-missing product classification from *category, majorcat*, or *department* or a detailed product description. These restrictions give us a sample of 54,404,892 unique items sold during the period 2019-2023. For these items, we have information on their classification: sub-category, category, major category, department, and sector (listed hierarchically from more detailed to more aggregated classification). An example here would be the "Adult Cough/Chest Congestion" sub-category in the "Adult Cold Cough & Flu" category, "Cold, Cough & Flu" major category, "Personal Health Care" department, and the "Health & Beauty" sector. For more than 20 million items in our sample, we have detailed product descriptions that provide more information about the packaging, weight, and other product attributes (e.g., CV MUCUS REL 30 CT).

We also construct another smaller sample for those items that again exclude the items classified in the "Limited Service Restaurant," "Restaurant," "Non-Item," "Unknown," or "Indeterminate Category" sector but have non-missing upc or gtin codes. This sample is mostly a subsample of our baseline sample described above and contains 4,979,163 items with more than half of items having detailed product descriptions.

Figure **??** shows the number of stores across various distribution channels in the data, while Figure A.1 shows expenditure shares and the number of unique item id's by broadly defined sectors in Numerator.

[2]Item is the finest product code available in Numerator. It is the product code that the data provider assigns based on what looks like distinct products, however because of the lack of detailed product descriptions and barcodes for many items, it is possible that exactly the same product is sold in different stores, but since it lacks barcode information, it has to be treated as different item by the Numerator.

**Table A.1.** Stores: Summary Statistic of Distribution Channel

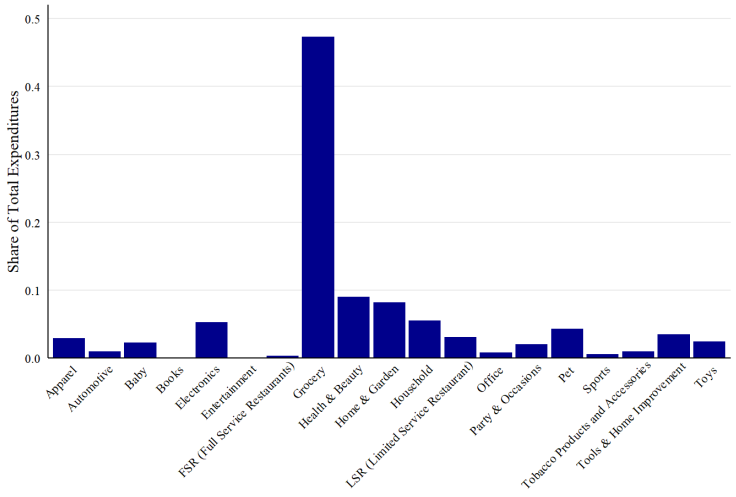
| Channel | Frequency | Percent | Cum. |
|---|---|---|---|
| Food | 10,142 | 20.85% | 20.85% |
| FSR - Regional/Ethnic | 8,428 | 17.32% | 38.17% |
| Gas & Convenience | 7,421 | 15.25% | 53.43% |
| Liquor | 2,905 | 5.97% | 59.40% |
| Bodega | 2,317 | 4.76% | 64.16% |
| Apparel | 1,692 | 3.48% | 67.64% |
| Drug | 1,471 | 3.02% | 70.66% |
| LSR - Bakery/Cafe | 1,270 | 2.61% | 73.27% |
| Beauty | 999 | 2.05% | 75.33% |
| Pet | 990 | 2.04% | 77.36% |
| Home Improvement | 819 | 1.68% | 79.05% |
| Craft | 701 | 1.44% | 80.49% |
| Online | 531 | 1.09% | 81.58% |
| Other | 515 | 1.06% | 82.64% |
| LSR - Ethnic/Regional | 512 | 1.05% | 83.69% |
| Dispensaries | 433 | 0.89% | 84.58% |
| Sporting Goods Stores | 424 | 0.87% | 85.45% |
| Postal Services | 401 | 0.82% | 86.27% |
| Other Retail Store | 390 | 0.80% | 87.08% |
| LSR - Coffee/Bakery | 385 | 0.79% | 87.87% |
| Book | 357 | 0.73% | 88.60% |
| Other Specialty Store | 331 | 0.68% | 89.28% |
| Dollar | 311 | 0.64% | 89.92% |
| Specialty Food Retailer | 300 | 0.62% | 90.54% |
| Mass | 237 | 0.49% | 91.03% |
| Health | 226 | 0.46% | 91.49% |
| Electronics | 219 | 0.45% | 91.94% |
| Shoe | 203 | 0.42% | 92.36% |
| Baby & Toy | 201 | 0.41% | 92.77% |
| Auto | 194 | 0.40% | 93.17% |
| LSR - Pizza | 192 | 0.39% | 93.56% |
| Department Store | 181 | 0.37% | 93.94% |
| FSR - Miscellaneous | 181 | 0.37% | 94.31% |
| LSR - Burger | 137 | 0.28% | 94.59% |
| Discount Store | 134 | 0.28% | 94.87% |
| Home Furnishings | 128 | 0.26% | 95.13% |
| Vapor Stores | 121 | 0.25% | 95.38% |
| FSR - Sports Bar | 106 | 0.22% | 95.59% |
| Tobacco Shops | 97 | 0.20% | 95.79% |
| Auto Services | 95 | 0.20% | 95.99% |
| Other Entertainment | 89 | 0.18% | 96.17% |
| Other Services | 85 | 0.17% | 96.35% |
| Office | 81 | 0.17% | 96.51% |
| Shopping Centers & Malls | 74 | 0.15% | 96.67% |
| Amusement Parks | 71 | 0.15% | 96.81% |
| Spas | 69 | 0.14% | 96.95% |
| LSR - Dessert Snack | 67 | 0.14% | 97.09% |
| Hotels & Resorts | 66 | 0.14% | 97.23% |
| CloseOut | 62 | 0.13% | 97.35% |
| Healthcare | 61 | 0.13% | 97.48% |
| Florists | 53 | 0.11% | 97.59% |
| LSR - Chicken | 53 | 0.11% | 97.70% |
| LSR - Mexican | 52 | 0.11% | 97.80% |
| LSR - Sandwich/Deli | 52 | 0.11% | 97.91% |
| Total | 47,631 | 97.91% | |

| Channel | Frequency | Percent | Cum. |
|---|---|---|---|
| Military | 49 | 0.10% | 98.01% |
| School Tuition & Fees | 49 | 0.10% | 98.11% |
| FSR - American | 46 | 0.09% | 98.21% |
| Sports & Recreation | 46 | 0.09% | 98.30% |
| Mortgage Payment | 44 | 0.09% | 98.39% |
| FSR - Midscale | 41 | 0.08% | 98.48% |
| Farm | 36 | 0.07% | 98.55% |
| Movie Theatre | 36 | 0.07% | 98.62% |
| Outlet Store | 36 | 0.07% | 98.70% |
| Sports Entertainment | 36 | 0.07% | 98.77% |
| Other Association Fees | 32 | 0.07% | 98.84% |
| Wireless | 32 | 0.07% | 98.90% |
| Charities | 31 | 0.06% | 98.97% |
| Video | 31 | 0.06% | 99.03% |
| FSR - Italian/Pizza | 29 | 0.06% | 99.09% |
| FSR - Seafood/Steak | 28 | 0.06% | 99.15% |
| LSR - Salad/Healthful | 28 | 0.06% | 99.21% |
| Transport Hub | 28 | 0.06% | 99.26% |
| Music Stores | 27 | 0.06% | 99.32% |
| Gambling | 24 | 0.05% | 99.37% |
| Professional Services | 24 | 0.05% | 99.42% |
| Veterinarians | 24 | 0.05% | 99.47% |
| Public Markets | 21 | 0.04% | 99.51% |
| Yard Services | 19 | 0.04% | 99.55% |
| Banks | 17 | 0.03% | 99.58% |
| Doctors Office | 17 | 0.03% | 99.62% |
| Wholesale | 17 | 0.03% | 99.65% |
| Club | 15 | 0.03% | 99.69% |
| Parking Lot or Garage | 15 | 0.03% | 99.72% |
| Laundromat | 13 | 0.03% | 99.74% |
| Airline | 11 | 0.02% | 99.77% |
| Other Travel | 11 | 0.02% | 99.79% |
| Telecom | 10 | 0.02% | 99.81% |
| Utility Company | 10 | 0.02% | 99.83% |
| Media | 9 | 0.02% | 99.85% |
| Real Estate Services | 9 | 0.02% | 99.87% |
| Concert Hall or Theater | 8 | 0.02% | 99.88% |
| Other Government Payments | 8 | 0.02% | 99.90% |
| Child Care | 7 | 0.01% | 99.91% |
| Retail Services | 7 | 0.01% | 99.93% |
| Church Offerings | 5 | 0.01% | 99.94% |
| Car Rental | 4 | 0.01% | 99.95% |
| Copy Centers | 4 | 0.01% | 99.95% |
| Public Storage | 3 | 0.01% | 99.96% |
| Security Services | 3 | 0.01% | 99.97% |
| Taxi or Limousine | 3 | 0.01% | 99.97% |
| Travel Agency | 3 | 0.01% | 99.98% |
| Bakery | 2 | 0.00% | 99.98% |
| Cruise Line | 2 | 0.00% | 99.99% |
| Dance & Comedy Clubs | 2 | 0.00% | 99.99% |
| Bar or Night Club | 1 | 0.00% | 99.99% |
| Movers | 1 | 0.00% | 100.00% |
| Ticket Outlet | 1 | 0.00% | 100.00% |
| Unknown | 1 | 0.00% | 100.00% |
| Total | 48,648 | 100.00% | |

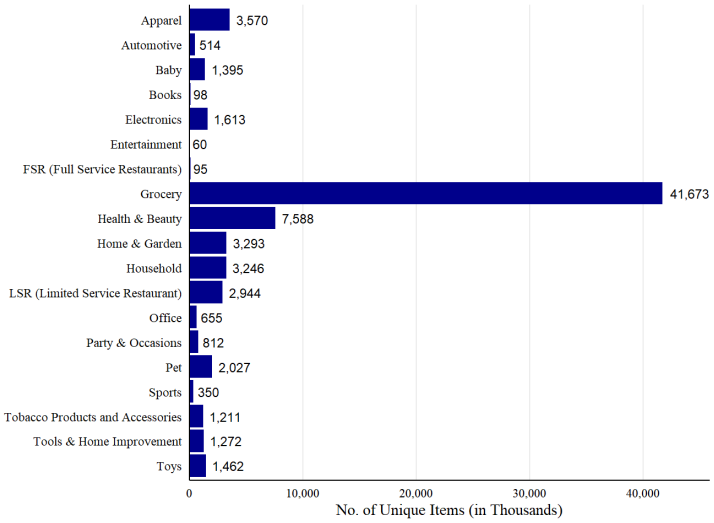
*Notes*: Each Banner (48.648 here) does not represent a physical store location. It represents someway in which a given retailer sells. For the retailer Walmart, there is one banner called Walmart which represents the traditional walmart supercenter, but there is also WalmartNeighborhood representing their smaller neighborhood stores, as well as a banner for their tire and lube division. Each of these banners, though belonging to the same retailer, may operate through a differnet one of the 108 channels listed in Figure A.1.

**Figure A.1.** Expenditures and Products by Sectors in Numerator

(A) Expenditure Shares by Sector



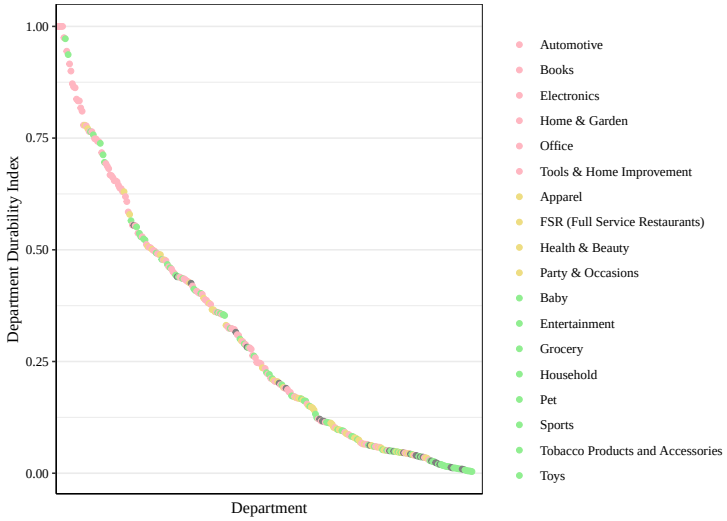

(B) Unique UPC's by Sector



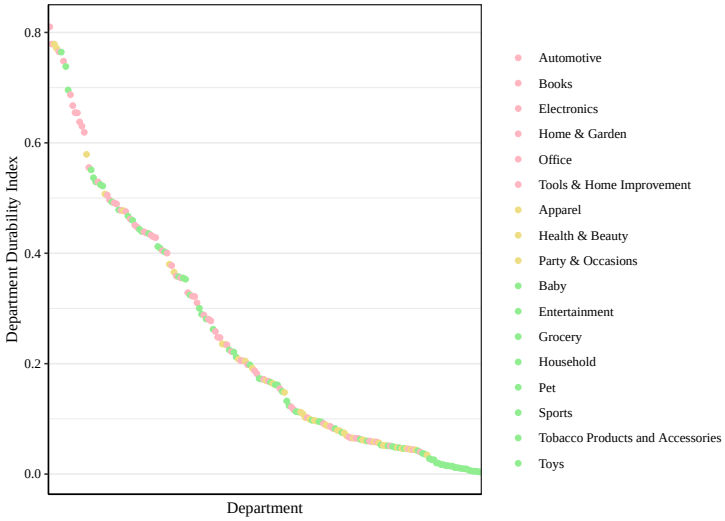

*Notes*: (A) Sample from non-missing brand and category information. Total expenditure is $4 billion from 683 million transaction-item observations in 2022. In 2022, the CEX described 12.8% of total expenditure, but 52.6% of expenditures amongst categories similar to those captured by Numerator. Numerator shows 47% of expenditure goes to Groceries. (B) Number of unique items by sector from non-missing brand and category information.

**Figure A.2.** Department Level Durability Indecies

(A) Durability by Department (Full Sample)




(B) Durability by Department (Selected Sample)




*Notes*: (A) Durability of all 306 available department descriptions. Colors indicate how durable a department would seem to be, not based on the data here. Pink represents the highest durability category, followed by yellow, then green as the least durable. Gray dots represent sectors that are not easily classifiable like indeterminate products and non-items. (B) Durability of all 188 departments found after dropping departments and sectors we are not interested in, like restaurants.

**Table A.2.** Top 20 and Bottom 20 Departments based on Durability

| Department | Sector | Durability Index |
|---|---|---|
| Architecture & Design | Books | 1.000 |
| Birthday | Toys | 1.000 |
| Business Office Furniture | Office | 1.000 |
| Office Lighting | Office | 1.000 |
| Posters | Books | 1.000 |
| Sustainability | Books | 1.000 |
| Celebrate Childrens Books | Books | 0.975 |
| Miscellaneous (Books) | Books | 0.975 |
| Parenting & Families | Books | 0.966 |
| Pressure & Temperature | Tools & Home Imp. | 0.959 |
| Performing Arts | Books | 0.945 |
| Romance | Books | 0.911 |
| Carrying Cases | Office | 0.910 |
| Biography & Memoirs | Books | 0.909 |
| Office Furniture & Lighting | Office | 0.896 |
| Stationary (Baby) | Baby | 0.890 |
| Pregnancy & Maternity | Baby | 0.859 |
| Sports & Recreation (Books) | Books | 0.836 |
| Travel & Nature (Books) | Books | 0.833 |

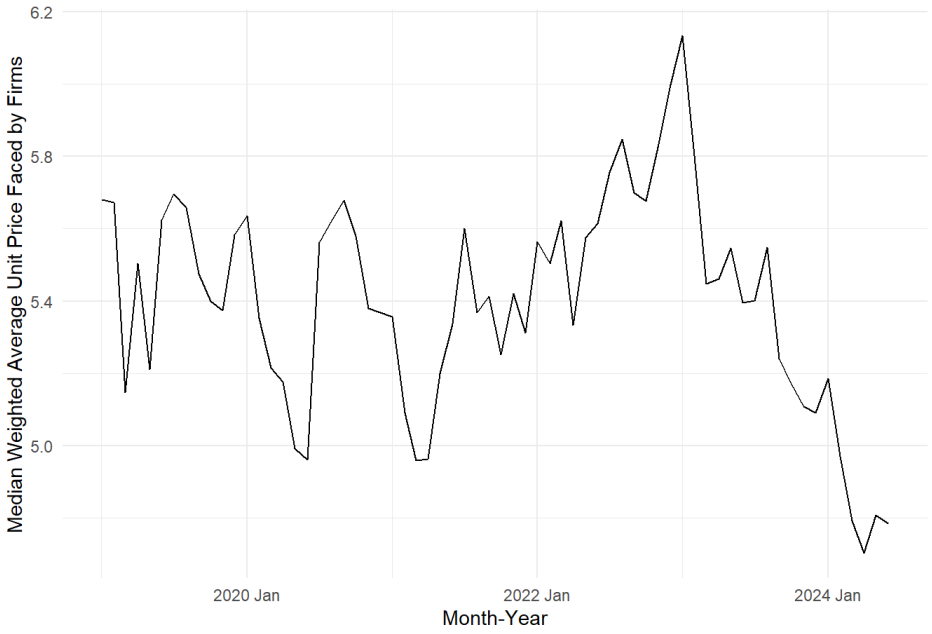
| Department | Sector | Durability Index |
|---|---|---|
| Paper & Plastic | Household | 0.017 |
| Lottery | Non-Item | 0.017 |
| LSR Beverages | LSR | 0.017 |
| Packaged Bakery (Bread & Alternative) | Grocery | 0.016 |
| Canned | Grocery | 0.016 |
| Shelf Stable Meals | Grocery | 0.016 |
| Alcohol Beverages | Grocery | 0.014 |
| Baking & Cooking | Grocery | 0.012 |
| Combustible Nicotine Products | Tobacco | 0.011 |
| Candy (Snacks) | Grocery | 0.011 |
| Meat | Grocery | 0.009 |
| Infant Toddler Nutrition | Baby | 0.009 |
| Frozen Foods | Grocery | 0.008 |
| Snack | Grocery | 0.006 |
| Pet Food & Treats | Pet | 0.006 |
| Dairy | Grocery | 0.005 |
| Beverages | Grocery | 0.005 |
| Mobile App Downloads | Electronics | 0.005 |
| Produce | Grocery | 0.003 |

*Notes*: Tools & Home Imp: Tools and Home Improvement. LSR: Limited Service Restaurant. Tobacco: Tobacco Products and Accessories.

Durabilities constructed out of the 2023 Numerator transaction data. We use a subset of the data containing only those involved in the static panel and who were in the panel for 12 consecutive months in 2023. We then construct a count, by person, of the number of transactions for each department. Averaging across the users tells us how many transactions the average static panelist made for a given department. Finally, the durability index is simply the inverse of the mean number of transactions per person for a given department.

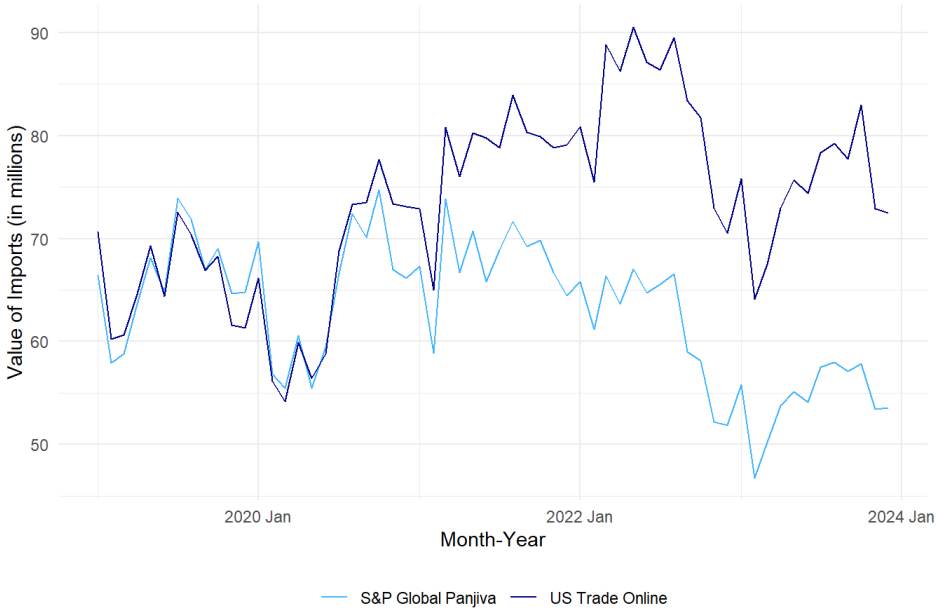
## B.2 BoL Panjiva Data

**Figure A.3.** Import Price Index

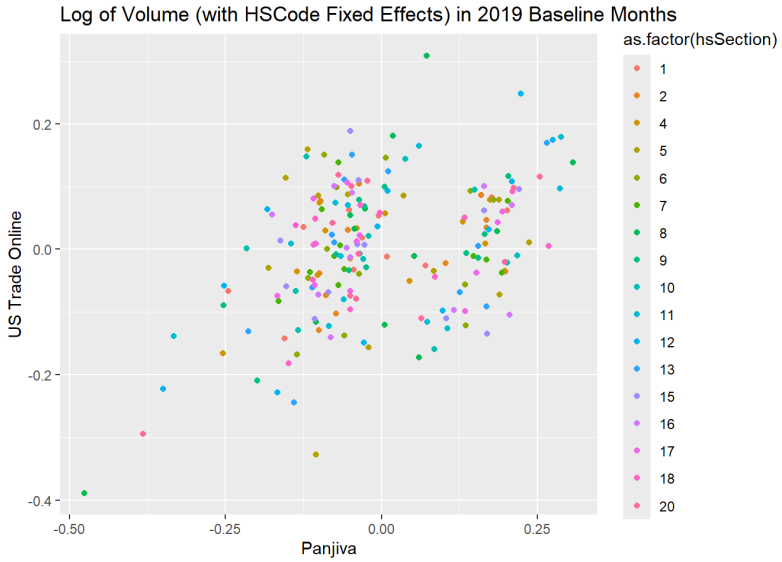



*Notes*: The median import price index faced by firms in BoL. Fixing the 2019 2-digit HS-code import shares of the firms, we calculate the weighted mean of the average import price for each firm and then plot the median of this value over time.

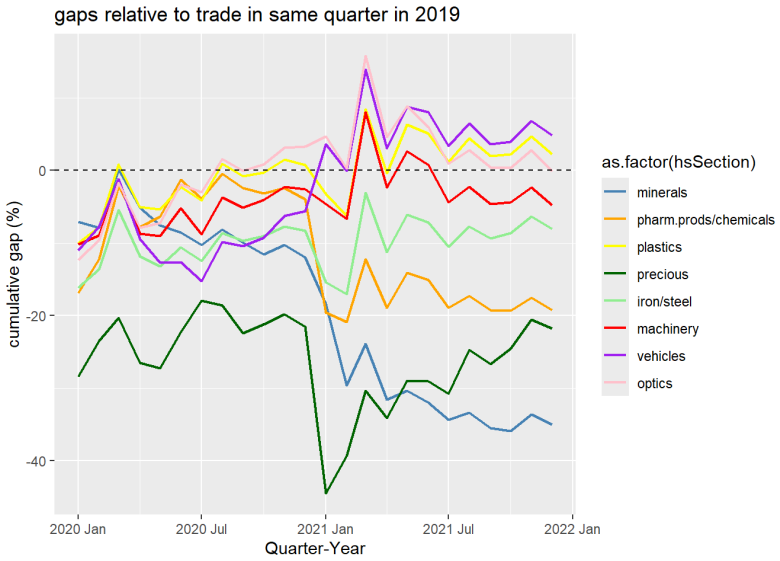
**Figure A.4.** US Imports over Time. Panjiva vs. Census. Firms with delivery shortfall measures.




*Notes*: Total imports of a sample of firms with non-missing delivery delay measures in BoL Panjiva against USA Trade Online - U.S. Census Bureau imports data. Panjiva import volumes are indexed to the 2019 unit value of an HS code in Census data.




*Notes*: Panjiva aggregate trade volumes compared to US Trade online aggregate trade volumes, residualized with HS code fixed effects (Census, 2023, own calculation)




*Notes*: Cumulative gap in aggregate imports by select HS2 categories, compared to cumulative in 2019 baseline (Panjiva, own calculation).

## B.3 Numerator-BoL Panjiva Match

We match Numerator and BoL Panjiva datasets at both the *firm* and *firm-HS code* levels, providing a comprehensive link between product-level prices and international shipment data.

**Firm-level match.** The first step in linking the datasets is to match firms in Numerator with those in BoL Panjiva using company names. In BoL, we primarily use consignee names as our firm identifier, which often represent the manufacturing companies but can also include retailers directly receiving shipments. In some instances, U.S. multinational firms ship products directly to U.S. stores from abroad. To capture these cases, we also include shipper names from the Bill of Lading, ensuring that our firm identifiers in Panjiva reflect both consignees and shippers.

In Numerator, each product entry can be associated with multiple names, including manufacturer, parent brand, and brand names, offering several options for identifying producers. Manufacturer names are frequently missing on scanned receipts, with data providers focusing on supplementing this information for high-sales products. As a result, larger firms are more likely to have this data, while it may be absent for smaller firms or less significant products. Our sample contains 9,569 unique manufacturer names, 70,205 unique parent brand names, and 85,903 unique brand names. Examples of entries include:

- PROCTER & GAMBLE COMPANY / REGENERIST OLAY / OLAY
- PRIVATE LABEL / PRIVATE LABEL / WALMART
- LEGO SYSTEMS, INC / DISNEY LEGO / LEGO
- APPLE INC. / APPLE / APPLE WATCH SERIES 8

These combinations of manufacturer, parent brand, and brand names provide a strong foundation for matching with the firm names reported in Panjiva. Additionally, Numerator's list of approximately 27,000 store names helps identify Panjiva shipments whose direct receivers are the retail stores. After compiling company names from both datasets, we clean and standardize the names to ensure consistency and comparability. We build on existing name-cleaning routines, such as those developed by Argente et al., and add steps specific to the peculiarities of Panjiva strings. This includes removing city, country, and zip code information that often appears in consignee names (e.g., "LG ELECTRONICS PANAMA S.A." or "TARGET ATLANTA GEORGIA 30309 USA").

We start from the Numerator data, where the unit of observation includes the manufacturing name, parent brand, and brand name. We perform an exact match with Panjiva consignee and shipper names using a hierarchical approach: first matching the manufacturer name, followed by the parent brand, and finally the brand name. If no matches are found with consignee names, we extend the matching to shipper names in the same hierarchical order. This process allows us to establish comprehensive links between the two datasets, enabling the analysis of firm-level price changes in relation to import activity.

**Firm-HS code match.** For a more granular match, we link firms and HS codes in Panjiva with products in Numerator at the firm-HS code level. In Panjiva, each shipment is associated with HS codes, providing a detailed classification of the imported goods. However, some shipments include multiple HS codes, complicating the assignment of shipment value to specific codes. Therefore, in our firm-HS code match, we exclude shipments with multiple HS codes to maintain accuracy.

Numerator data, by contrast, do not include direct HS code classifications. Instead, they offer hierarchical product descriptions, such as “COLORED PENCILS / DRAWING, PAINTING & SKETCHING SUPPLIES / ARTS & CRAFTS / TOYS,” sometimes with more specific details like “PRISMACOLOR SCHOLAR COLORED PENCIL SHARPENER.” To bridge this gap, we use text analysis techniques to classify Numerator products into corresponding HS codes, enabling a consistent and comparable match across the datasets.

# C Additional Empirical Results

**Table A.3.** Pass-Through of Delivery Shortfalls to Prices, Weighted

| | Price change | Price change | Price change |
|---|---|---|---|
| Shortfall | -0.005*** | | |
| | (0.0009) | | |
| Shortfall, Shift-Share | | -0.056*** | |
| | | (0.0136) | |
| Shortfall, IV | | | -0.310*** |
| | | | (0.0755) |
| I-stage F-stat | | | 22 |
| Firm FE | ✓ | ✓ | ✓ |
| Cat-Year-Quarter FE | ✓ | ✓ | ✓ |
| R squared | 0.182 | 0.182 | 0.182 |
| Observations | 453619 | 453619 | 453619 |

Notes: 12-month price changes at the product (firm-brand-category) level on delivery shortfalls (12-week moving average) at the firm level. All variables are in percent change. Column 1 estimates specification (7); column 2 corresponds to (8); column 3 corresponds to estimates from (9). Regressions weighted with firm-level average sales. Robust standard errors in parentheses are clustered at the product level.

**Table A.4.** Pass-Through of Delivery Shortfalls to Prices. Firm-level

| | (1) Price change | (2) Price change | (3) Price change |
|---|---|---|---|
| Shortfall | -0.004 | | |
| | (0.0035) | | |
| Shortfall, Shift-Share | | -0.038 | |
| | | (0.0448) | |
| Shortfall, IV | | | -0.075 |
| | | | (0.0896) |
| I-stage F-stat | | | 25 |
| Firm FE | ✓ | ✓ | ✓ |
| Year-Month FE | ✓ | ✓ | ✓ |
| R squared | 0.263 | 0.263 | 0.263 |
| Observations | 47169 | 47169 | 47169 |

Notes: 12-month price changes at the firm-month level on delivery shortfalls (12-week moving average) at the firm-month level. All variables are in percent change. Column 1 estimates specification (7); column 2 corresponds to (8); column 3 corresponds to estimates from (9). Robust standard errors in parentheses are clustered at the product level.

**Table A.5.** Pass-Through of Delivery Shortfalls to Prices with Various Lags. Firm-level

| | (1) Price change | (2) Price change | (3) Price change | (4) Price change | (5) Price change |
|---|---|---|---|---|---|
| Shortfall, IV | -0.075 | | | | |
| | (0.0896) | | | | |
| L.Shortfall, IV | | -0.165* | | | |
| | | (0.0921) | | | |
| L2.Shortfall, IV | | | -0.251*** | | |
| | | | (0.0926) | | |
| L3.Shortfall, IV | | | | -0.278*** | |
| | | | | (0.0873) | |
| L5.Shortfall, IV | | | | | -0.262*** |
| | | | | | (0.0724) |
| Firm FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year-Month FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| R squared | 0.263 | 0.282 | 0.300 | 0.327 | 0.380 |
| Observations | 47169 | 41457 | 40200 | 39893 | 36404 |

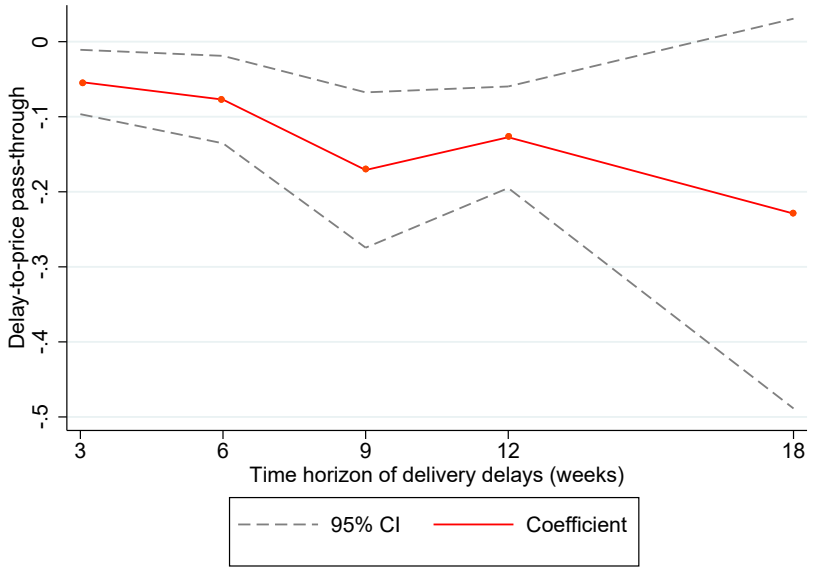
Notes: 12-month price changes at the firm-month level on delivery shortfalls (12-week moving average) at the firm-month level. Different columns show different lags of the IV variable. All variables are in percent change. Column 1 estimates specification (7); column 2 corresponds to (8); column 3 corresponds to estimates from (9). Robust standard errors in parentheses are clustered at the product level.

**Table A.6.** Pass-Through of Delivery Shortfalls to Prices. Durability

| | Price change OLS | Price change OLS | Price change IV | Price change IV |
|---|---|---|---|---|
| Shortfall | -0.001** | | | |
| | (0.0005) | | | |
| Shortfall, Shift-Share | | -0.029*** | | |
| | | (0.0074) | | |
| Shortfall, IV | | | -0.130*** | -0.131*** |
| | | | (0.0334) | (0.0331) |
| Shortfall × Durability | 0.003 | 0.121* | 0.542* | 0.112* |
| | (0.0046) | (0.0686) | (0.3086) | (0.0610) |
| Durability | 8.591** | 8.580** | 9.316** | 0.243** |
| | (4.3787) | (4.3758) | (4.3799) | (0.1107) |
| Firm FE | Yes | Yes | Yes | Yes |
| Cat-Year-Quarter FE | Yes | Yes | Yes | Yes |
| R squared | 0.149 | 0.149 | 0.149 | 0.149 |
| Observations | 448776 | 448776 | 448776 | 448776 |

Notes: 12-month price changes at the product (firm-brand-category) level on delivery shortfalls (12-week moving average) at the firm level and durability measure and its interaction with delivery shortfalls. The durability index is used in columns (1)-(3) and is defined at the department level (see construction in Appendix **??**). A durability dummy used in column (4) is a dummy variable equal to one for departments above the top quartile of durability distribution across different products. The dependent variable and Shortfall are in percent changes. Column 1 estimates specification (7); column 2 corresponds to (8); column 3 corresponds to estimates from (9). Robust standard errors in parentheses are clustered at the product level.

**Figure A.5.** Pass-Through over Different Horizons of Delivery Shortfalls




Notes: Coefficients from the separate IV regressions (equation (9)) of 12-month price changes at the product (firm-brand-category) level on firm-level delivery shortfalls in moving averages at different horizons(in weeks). Robust se clustered at the product level. All variables are in growth rates.