Supply Chain Shocks and Retail Resilience: The Dynamics of Global Value Chains and Inventories

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We examine the role and relationship of global value chains and inventories by delving into the dynamic effects of upstream manufacturing shocks on downstream retailer performance. Motivated by the pivotal role inventories play in firm demand management, our research employs a novel two-step methodology involving a reduced-form semiparametric smooth coefficient model, and a structural vector autoregressive model. The findings, based on monthly data spanning from January 1999 to December 2021, reveal a profound, and enduring impact of manufacturing supply chain shocks on the retail sector. Following a unit supply chain shock, downstream retailers experience a substantial and lasting increase in inventory accumulation, accompanied by a short-term decline, and subsequent stabilization in sales. Moreover, post-shock, retailers experience a permanent decrease in output, underscoring the far-reaching, and persistent consequences of disruptions in upstream supply chain agents on downstream retail operations.

Keywords: supply chains, inventories, semiparametric, Time Series, supply shocks

INTRODUCTION

Using macroeconomic data on aggregate manufacturer and retailer inventories and sales, we ask ourselves how resilient retailers in the United States are to supply chain shocks originating upstream from manufacturers. To this end, we leverage a two-step procedure to identify our supply chain shock upstream, and then simulate the responses of retailer inventories, sales, and production to such a perturbance.

Global value chains, which link customer-facing downstream retailers with upstream manufacturing suppliers, are extensively studied in existing research in both the fields of economics and operations research (Metters, 1997; Lee et al., 1997; Bray & Mendelson, 2013). However, the transmission mechanisms of upstream shocks in the manufacturing sector and their subsequent impacts on downstream retailers at a macroeconomic lack clear exposition. This paper aims to address this gap by identifying and quantifying the effects of upstream manufacturing shocks on retailer inventory investment, sales growth, and production using monthly data from January 1999 through December 2021.

Looking at the inventories literature, there are several works that offer foundations that supply chain research is quite compatible with. First and foremost is the Handbook of Macroeconomics chapter, Ramey & West (1999), which provides a summary of the literature and an extensive analysis of the empirical models that are the backbone of the literature, including the flexible accelerator model, and buffer-stock model. The authors of this work call to attention five key fronts motivating future research in the inventories sphere: persistence of sales, persistence of inventories, adjustment speeds of inventories, the relative volatility of inventories and production, and the nature of the cointegrating relationship between inventories and sales.

Works like Bils & Kahn (2000) and Wen (2011) pay special attention to the adjustment speed puzzle, which is still an ongoing point of focus in recent inventories research. In this context, adjustment speed refers to the speed at which inventories re-adjust or error-correct to equilibrium levels after a sales shock (demand shock). Typically, findings on the speed of adjustment indicate that it is relatively slow, and in some studies, non-existent.

The sluggishness of adjustment speeds has been attributed to countercyclical markups in the case of Bils & Kahn (2000) but have also been explored in related works like Crouzet & Oh (2015) and Jones & Tuzel (2013) for reasons other than markups alone. More recently, inventories have been viewed through the lens of productivity researchers, and in works like Gortz et al. (2022) and Gortz & Gunn (2018) who note that inventory comoves with total factor productivity in the presence of specific shocks—in the case of these studies data settings, news shocks.

With this background in mind, in the first step of our analysis, we employ a reduced-form semiparametric smooth coefficient estimation approach to model the manufacturing sector's response to various environmental factors, including the global supply chain pressure index and economic activity indicators. Specifically, we utilize three environmental factors that capture aggregate supply chain stress, including the global supply chain pressure index, the Kilian (2009) index of economic activity, and the Wu & Xia (2016) shadow rate. This procedure allows us to map these coefficients to structural parameters approximating supply chain disturbances. In the second step, we construct a three-variable structural vector autoregressive model to examine the relationship between retailer inventory investment, sales growth, and the identified supply chain shock.

Our investigation is motivated by the literature on inventories, which play a crucial role in firm demand management and are closely tied to supply chain dynamics and business cycle fluctuations (Abramovitz, 1950; Blinder et al., 1981; Blanchard, 1983). Previous studies have highlighted the significant impact of supply chain stress on inventory management and business cycle volatility. Despite advancements in understanding supply chain resilience (Wieland & Durach, 2021; Tukamuhabwa et al., 2015), sources of supply chain distortions (Niranjan et al., 2011; Inoue & Todo, 2019), and the evolution of conceptual frameworks for supply chain resilience (Pettit et al., 2010; Scholten & Schilder, 2015), there remains a gap in connecting aggregate supply chain phenomena with macroeconomic performance and indicators.

To address this, we focus on the resilience of U.S. retailers to upstream supply chain shocks, leveraging macroeconomic data on manufacturer and retailer inventories and sales. By employing a two-step procedure, we aim to identify the upstream supply chain shock and simulate its effects on retailer inventories, sales, and production. Our findings reveal that supply chain shocks originating from manufacturers have substantial reverberations downstream, leading to long-term shifts in inventory levels, short-term sales declines, and permanent decreases in retail output. This underscores the importance of considering supply chain dynamics in macroeconomic analysis and policymaking.

A BASIC FLEXIBLE ACCELERATOR MODEL

To identify manufacturing sector supply chain shocks, we precede reduced-form analysis with a basic structural flexible accelerator model as originally described in Lovell (1961) and discussed in greater detail in Ramey & West (1999) and more recent works like Williams (2022), which characterizes a firm's inventory decision rule based on exogenous sales, and deviations of realized inventories from target inventory levels.

Consider the representative firm's objective function is described by equation (1). The assumption that sales are exogenous is consistent with previous macroeconomic inventory models across the literature. The argument for sale exogeneity is that at the beginning of any given period, sales are not known, but inventory stocks are, thus sales represent realized demand, which is categorically exogenous. One may counter that the presence of inventories generates demand, thereby making this assumption restrictive. However, we would argue that such a restriction is consistent with reality in that exogenous sales can create backlogged sales for firms, which is costly in opportunity.

$$\underset{H_t}{\arg\min}\left\{\frac{1}{2}(H_t - H_t^*)^2 + \frac{1}{2}\mu(H_t - H_{t-1})^2 + \varepsilon_t H_t\right\} \tag{1}$$

where $\mu > 0$ is the weight of the second cost term relative to the first, and ε_t is a disturbance term—we pay particular attention to this term, which contains valuable information on structural variation in inventory levels and is assumed to be $\sim \mathcal{N}(0, \sigma^2)$. The first-order condition (FOC) with respect to H_t yields equation (2). The idea behind this model, however stylized, is that firms seek to minimize inventory carry costs relative to some target level of inventories. Firms neither want to hold excess inventories, which bear a direct monetary cost, nor do they want too few inventories, which can risk generating sales backlog or lost sales.

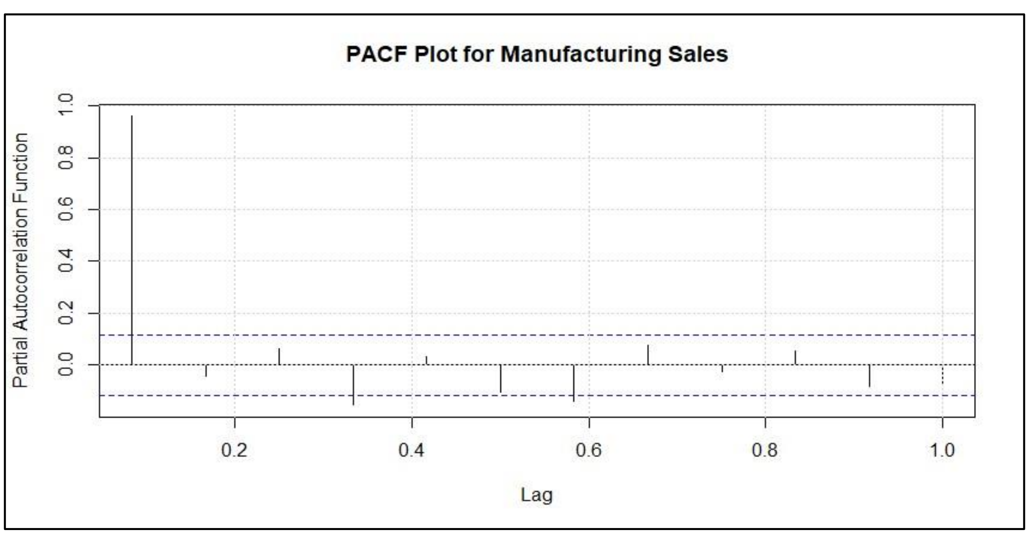
$$H_t - H_{t-1} = [1/(1+\mu)](H_t^* - H_{t-1}) - [1/(1+\mu)]\varepsilon_t \tag{2}$$

where the term $\frac{1}{1+\mu}$ represents the gap between the target and starting inventory levels within a given period. To complete this model, and derive a decision rule, target inventory levels, H_t^*, must be defined. Typically, it is common to assume thst target inventory levels are some θ proportion of sales such that $H_t^* = \theta S_t$, where S_t are sales in the current period—in a sense, θ somewhat captures the inventory-to-sales relationship.

A secondary somewhat strong assumption regarding this parameter is that it implies that the inventories-to-sales relationship is relatively constant over time. There is some debate in the literature regarding the strength of the cointegrating relationship between inventories and sales over time, although many works (Granger and Lee, 1989; Hamilton, 2002; Williams, 2022) favorably identify a long run cointegrating relationship between inventories and sales that is, definitionally, constant.

Finally, S_t must be given an explicit law of motion, the easiest being a simple autoregressive representation such as $S_t = S_{t-1} + e_t$. This law of motion is once more consistent with past stylizations of sales but is verifiable in most sales data itself. At the manufacturing level, from the M3 survey in the United States, most domestic manufacturers express a PACF plot of the variety described in Figure 1, which is highly autoregressive to the first lag order.

FIGURE 1
PACF PLOT FOR MANUFACTURING SALES



Plugging back both the inventory-to-sales relationship and sales law of motion into the model and simplifying once more, we arrive at equation (3).

$$H_t - H_{t-1} = [1/(1+\mu)](\theta S_{t-1} + \theta e_t) - [1/(1+\mu)]H_{t-1} - [1/(1+\mu)]\varepsilon_t \tag{3}$$

Algebraic manipulation reduces equation (3) to equation (4) such that:

$$H_t = [1/(1+\mu)]\theta S_{t-1} + [1/(1+\mu)]\theta e_t - [1/(1+\mu)]H_{t-1} + H_{t-1} - [1/(1+\mu)]\varepsilon_t \tag{4}$$

Collecting similar terms, we arrive at equation (5):

$$H_t = [\theta/(1+\mu)]S_{t-1} + [\mu/(1+\mu)]H_{t-1} + [1/(1+\mu)](\theta e_t - \varepsilon_t) \tag{5}$$

Finally, we can express (5) in a reduced form described by equation (6):

$$H_t = \pi_S S_{t-1} + \pi_H H_{t-1} + u_t \tag{6}$$

In essence, the reduced-form solution for H_t is a simple autoregressive distributed lag model of order one—an ARDL(1,1). We can map our reduced-form parameters to the following structural parameters: $\pi_S = \frac{\theta}{1+\mu}$, $\pi_H = \frac{\mu}{1+\mu}$ and with $u_t = \frac{1}{1+\mu}(\theta e_t - \varepsilon_t)$ as the disturbance term.

It is also worth discussing that the key component of this structural model is the nature of $H_t - H_t^*$, which is somewhat endogenous depending on how H_t^* is defined. If H_t^* is a non-zero target based on autoregressive sales, then several outcomes can occur:

- *Scenario 1*: $H_t - H_t^* > 0$
  - This scenario implies that manufacturers are accumulating excess inventory above their target, which exacerbates carry costs.
- *Scenario 2*: $H_t - H_t^* < 0$
  - This scenario implies that manufacturers do not have enough inventory on hand to meet their target and are therefore risk losing or backlogging potential sales. This carries with it an *opportunity* cost, rather than a direct monetary cost.
- *Scenario 3*: $H_t - H_t^* = 0$
  - Ideally, manufacturers strive for this outcome, which is most efficient and cost-minimizing.

Looking downstream, manufacturers who find themselves in *Scenario 1* or *Scenario 2* put pressure on retailers in some manner or another. If manufacturers accumulate excess inventories, they may curtail production in future periods and try to burn down excess inventory stock. In the case of a positive supply chain shock or a sales shock downstream, manufacturer underproduction can leave retailers unable to service existing demand at their level. If in *Scenario 2*, a positive sales shock downstream will cause under-fulfillment, leading to an immediate shortage to retailer channels. Neither of these scenarios are ideal for firm, nor consumer welfare.

Ultimately, in our analysis, we seek to unravel the nature of the implied shock faced by retailers stemming from upstream manufacturers. Fundamentally, the interpretation of our shock simulations inform us as to whether firms are behaving in a manner that puts more weight on the costs associated with excess inventory accumulation or the opportunity cost of missed sales. If missed sales are more costly than carry costs in the aggregate sensem we would expect firms to engage in inventory hoarding in the presence of shocks—the buffer stock motive—to minimize potential sales losses even if it comes at the cost of excess inventory accumulation.

SHOCK IDENTIFICATION

A reduced-form approximation of equation (6) can be achieved by estimating an ARDL(p, q) model. We consider that there are many factors that can affect inventory levels in equilibrium within the manufacturing environment that are not explicitly captured by the flexible accelerator framework described equation (1), nor necessarily linear in relationship inventory or sales levels. Omission of these key environmental factors reduces the degree to which u_t can approximate "supply chain shocks" to inventory decision rules employed by firms farther downstream. To better identify this structural parameter, we employ a semiparametric smooth coefficient (SPSC) model variation of our ARDL(p, q) framework.

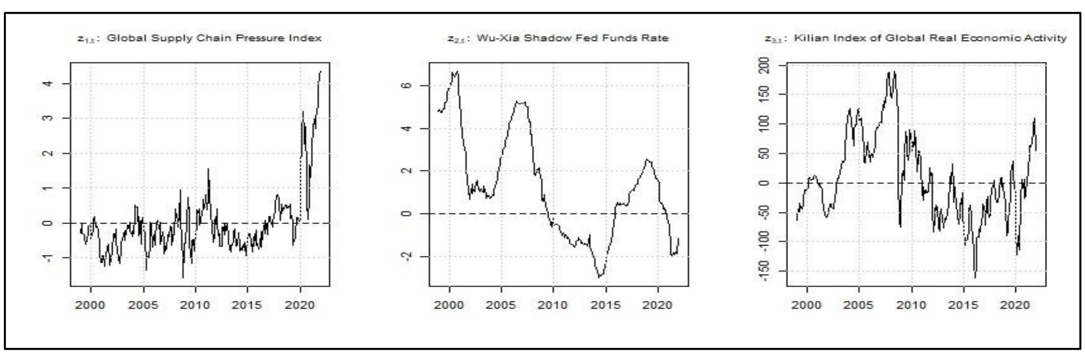
The SPSC model considers the possibility that the classic linear regression model estimated via ordinary least squares varies smoothly by some vector of environmental factors, Z_t. Thus $y = B_0 + B_1 x_1 + B_j x_j + \eta$ is instead expressed as $y_i = B_0 + B_1(Z) x_{1,i} + B_j(Z) x_{j,i} + \eta$, where our vector of varying coefficient estimates of $\hat{B}(Z)$ are obtained as $\hat{B}(Z) = \left[\sum_{i=1}^{n} \tilde{x}_i^T \tilde{x}_i K_i(Z)\right]^{-1} \times \left[\sum_{i=1}^{n} \tilde{x}_i^T \hat{y}_i K_i(Z)\right]$, where $\widetilde{x_i}$ is our vector of j independent variables of with $i = 1$ to n observations. See Hastie & Tibshirani (1993) and Li et al. (2002) for more exposition on SPSC models. $K_i(z) = K\left(\frac{Z_i - Z}{h}\right)$ describes a kernel density weighting of our environmental variable Z evaluated at each Z_i point.

To be explicit, h is the bandwidth selected via least-squares cross-validation (LSCV), and our kernel density function $K_i(\cdot)$ is that of a Gaussian or normal kernel. With this in mind, we estimate equation (6) as a varying coefficient ARDL(3,7), where $p = 3$, and $q = 7$ are selected via the Akaike information criterion (AIC). Beyond this, data on manufacturer shipments, and inventories are retrieved from the US Census Bureau. The specific data pneumonics are "MNFCTRIMSA" and "MNFCTRSMSA." Data is deflated by the producer price index for all commodities, "PPIACO," retrieved from the Bureau of Labor Statistics. This specification is described by equation (7).

$$H_t = C_0(Z_t) + \sum_{p=1}^{3} \beta_p(Z_t) H_{t-p} + \sum_{q=1}^{7} \gamma_q(Z_t) S_{t-q} + \tau(Z_t) T_t + \epsilon_t \tag{7}$$

where $C_0(Z_t)$ is a varying drift term, and $\tau(Z_t)$ is a varying time trend. Our Z_t vector of environmental variables consist of three environmental factors that could broadly influence manufacturers' inventory levels, and by-extension, the production environment for upstream manufacturers: $z_{1,t}$ is the global supply chain pressure index (GSCPI) published by the New York Fed, $z_{2,t}$ is the Wu & Xia (2016) shadow federal funds rate published by the Atlanta Fed, and $z_{3,t}$ is the Kilian (2009) index of global real economic activity published by the Dallas Fed. To avoid the curse of dimensionality that often plagues nonparametric, and semiparametric procedures, we limit the dimension of our Z_t vector to just three environmental variables, after which model convergence times grow too cumbersome. Figure 2 illustrates these environmental variables.

FIGURE 2
ENVIRONMENTAL FACTORS



Post-estimation, we can illustrate our varying coefficients graphically across all observations. Figure 3 conveys these coefficients. Table 1 shows the lower deciles and quartiles associated with each varying coefficient.

FIGURE 3
VARYING COEFFICIENTS

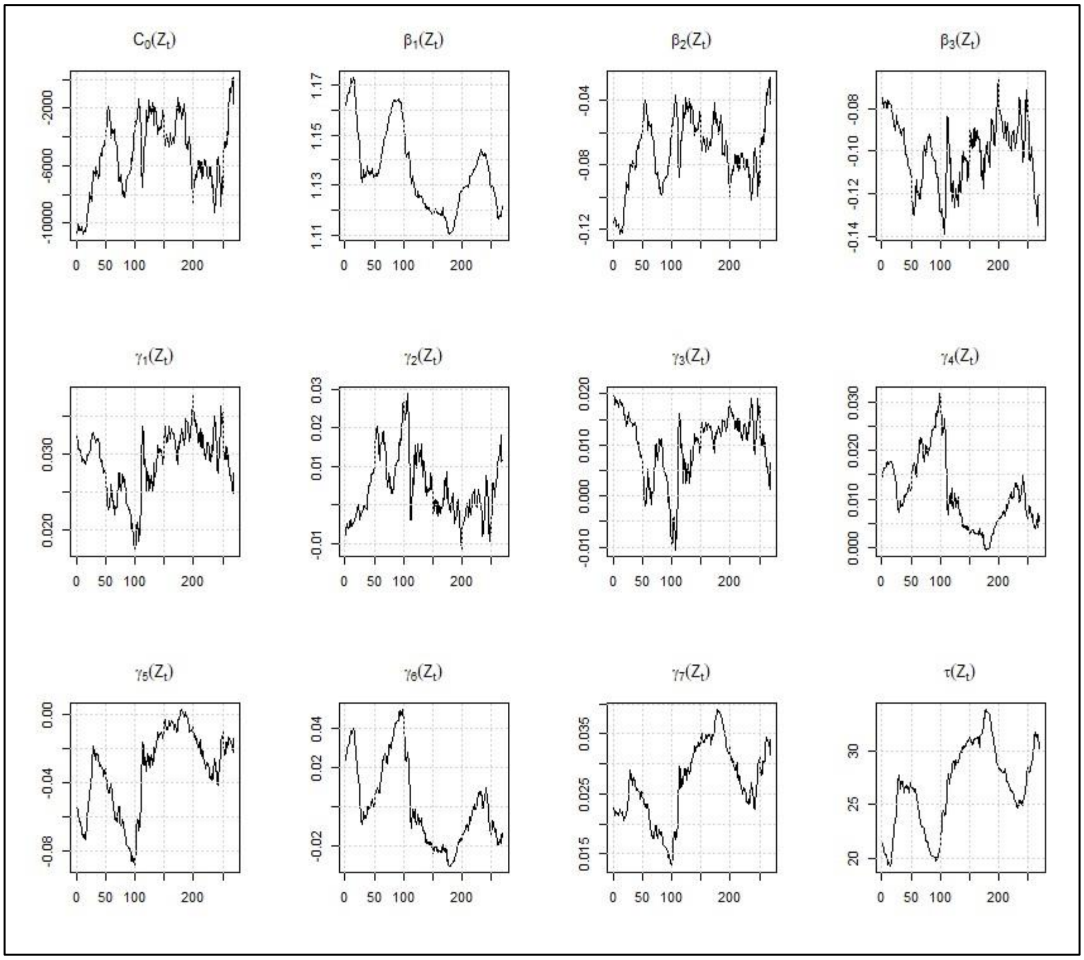
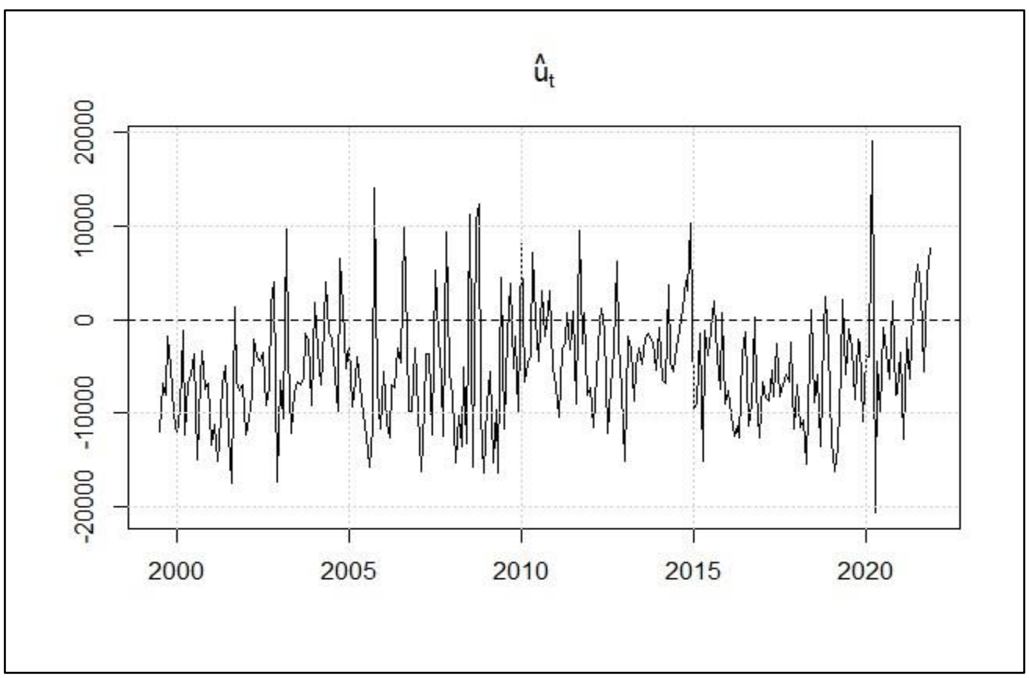


TABLE 1
FIRST STAGE VARYING COEFFICIENT RESULTS

Coefficient	Percentile					Other Moments	
	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	Mean	Std. Dev.
$C_0(Z_t)$	-8246.57	-6793.27	-4770.62	-3250.45	-2058.58	-5140.40	2506
$\beta_1(Z_t)$	1.12	1.12	1.13	1.14	1.16	1.14	0.02
$\beta_2(Z_t)$	-0.10	-0.08	-0.07	-0.06	-0.04	-0.07	0.02
$\beta_3(Z_t)$	-0.12	-0.11	-0.10	-0.09	-0.08	-0.10	0.02
$\gamma_1(Z_t)$	0.02	0.03	0.03	0.03	0.03	0.03	0.00
$\gamma_2(Z_t)$	0.00	0.00	0.00	0.01	0.02	0.00	0.01
$\gamma_3(Z_t)$	0.00	0.01	0.01	0.01	0.02	0.01	0.01
$\gamma_4(Z_t)$	0.00	0.01	0.01	0.02	0.02	0.01	0.01
$\gamma_5(Z_t)$	-0.07	-0.05	-0.03	-0.01	-0.01	-0.03	0.02
$\gamma_6(Z_t)$	-0.02	-0.02	0.00	0.02	0.04	0.00	0.02
$\gamma_7(Z_t)$	0.02	0.02	0.03	0.03	0.03	0.03	0.01
$\tau(Z_t)$	20.45	24.10	26.91	29.91	31.29	26.73	3.83

Note that from these varying coefficients, there is an implied mapping of $C_0(Z_t)$, $\tau(Z_t)T_t$, and ϵ_t to our structural disturbance term, u_t, in equation (6). Thus, we define our "manufacturing shock" as $\widehat{u_t} = C_0(Z_t) + \tau(Z_t)T_t + \epsilon_t$. By definition, since$C_0(Z_t)$, and $\tau(Z_t)T_t$ vary explicitly by our Z_t vector of environmental factors, so too does our disturbance term. It is also worth highlighting that the autoregressive coefficients vary minimally, however, the temporal components, including our drift term, and time trend vary considerably, and seem to be the most-heavily influenced by our environmental factors. This term should capture upstream shocks considerate of global supply chain conditions from manufacturers that reverberate downstream to retailers. Figure 4 captures this "shock" term.

FIGURE 4
ESTIMATE OF $\widehat{u_t}$



Fundamentally, our "supply chain shock" as identified captures unexplained variation manufacturer inventory investment that in-turn reverberates downstream subsequently impacting retailer inventory position and, consequently, sales or backlogged sales. While we acknowledge there are other variables that could affect inventory investment at a microeconomic level, they are not observable at a macroeconomic level, thus the choice of variables in the first stage of our shock identification are expressive of variables that could at a macroeconomic level affect manufacturer inventory investment decision in the aggregate sense.

Given that inventories are an investment that is realized as demand at later periods, we believe our compact set of environmental factors are appropriate. The Wu-Xia shadow rate captures monetary policy conditions, which directly impacts business investment, while the Kilian index approximates global economic activity, thereby proxying for trade, and transportation conditions, and finally, the supply chain pressure index should account for all other factors that would directly influence the transmission of manufacturer inventories to retailers outside of other controls.

DOWNSTREAM RESPONSES

To evaluate the downstream responses of retailers to supply chain disturbances originating upstream from manufacturers, we construct a simple structural vector autoregressive model (SVAR) with a lag order of $\rho = 2$ as per the AIC. Our SVAR(2) contains three variables: retail inventory investment (ΔH_t), retail sales growth (ΔS_t), and our upstream disturbance term ($\widehat{u_t}$). Formally, our SVAR(2) is defined compactly by equation (4.1). Retailer inventories, and sales data are retrieved from the US Census Bureau under the pneumonics "RETAILIMSA," and "RETAILSMSA," respectively, and deflated by the consumer price index ("CPIAUCSL") provided by the Bureau of Labor Statistics. Descriptive statistics are shown below in Table 2, including test results for variable stationarity. While not utilized in estimation of our SVAR(2), we also report descriptive statistics and stationarity tests (augmented Dickey-Fuller tests, specifically) for manufacturing sector data utilized in the first stage of our procedure. Data is collected monthly from January 1999 to December 2021 and measured in millions of US dollars.

TABLE 2
MODEL DATA AND DESCRIPTIVE STATISTICS

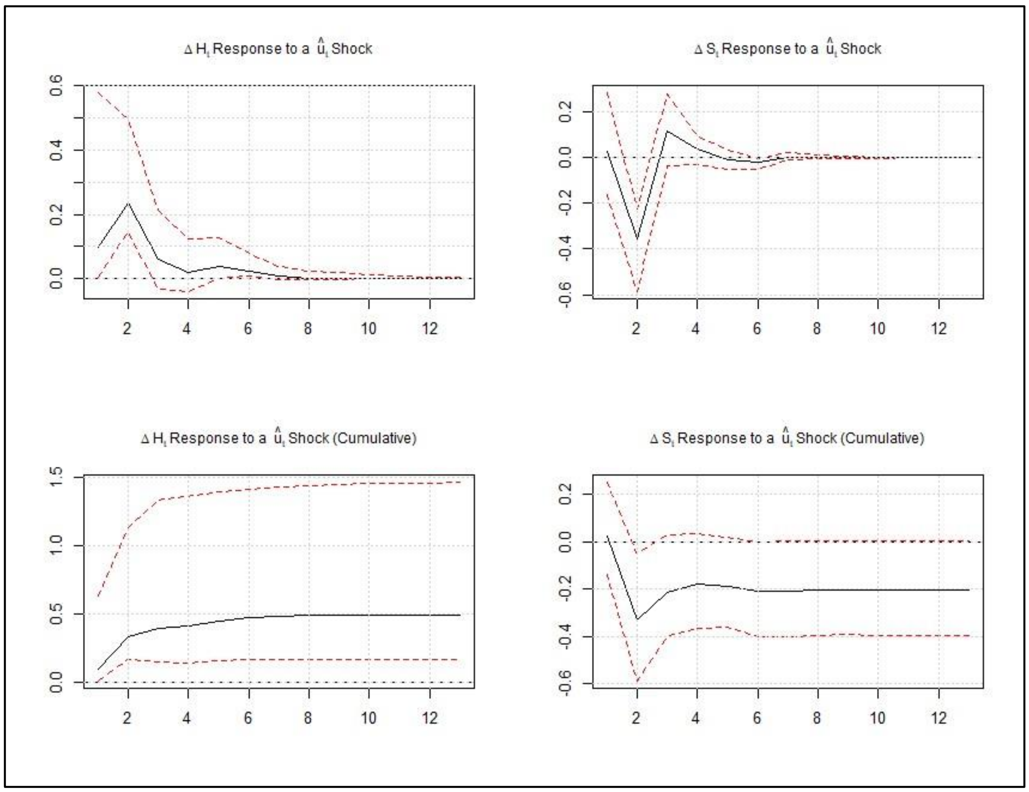
Supply Chain Position	Variable	Descriptive Statistics		ADF Test Statistics	
		Mean	Std. Dev.	Levels	First-Differences
Manufacturing	H_t	748096	46130.47	-2.27 (0.46)	-5.86 (0.00)
	S_t	563039.7	30053.65	-3.33 (0.07)	-5.83 (0.00)
	Q_t	562955.6	31524.7	-3.02 (0.14)	-5.77 (0.00)
Retail	H_t	651203.5	42929.47	-1.91 (0.64)	-5.42 (0.00)
	S_t	446411.1	41449.09	-0.84 (0.96)	-6.86 (0.00)
	Q_t	446845.5	41784.13	-0.78 (0.96)	-7.04 (0.00)

Not surprisingly, our data across all levels of our aggregated supply chain are stationary when first differenced, but test strongly as non-stationary in their levels. Furthermore, we note that across both manufacturers, and retailers, it is often the case that inventory levels far exceed both new production ($Q_t = S_t + \Delta H_t$), and sales. We do note that inventory volatility is comparable for both retailers and manufacturers, however, sales and production volatility are markedly lower for manufacturers compared to retailers. Equation (7) represents our reduced form SVAR(2) compactly.

$$A_0 Y_t = C_0 + \sum_{\rho=1}^{2} \Gamma_\rho Y_{t-\rho} + \tau T_t + \epsilon_t \tag{7}$$

where Y_t is a 3×1 matrix containing our endogenous variables such that $Y_t = [\Delta H_t, \Delta S_t, \widehat{u_t}]'$. A_0 is an impact matrix containing restrictions on the contemporaneous relationships among our endogenous variables. We opt for an upper-triangularization of this matrix, wherein ΔH_t responds contemporaneously to all innovations in our system, while $\widehat{u_t}$ does not respond contemporaneously to either inventory investment, nor sales growth, which makes it functionally "exogenous" for the purposes of identifying our structural innovations, which can be recovered by inverting A_0 such that $\varepsilon_t = A_0^{-1}\epsilon_t$. Transitory, and cumulative impulse-response functions are generated for sales growth, and inventory investment with specific attention given to responses of ΔS_t, and ΔH_t to one-unit shocks from $\widehat{u_t}$. Figure 5 shows these responses for up to twelve forecast periods (one year).

FIGURE 5
RESPONSES OF RETAILER INVENTORIES & SALES TO $\widehat{u_t}$ SHOCKS



Looking at transitory responses, we see that in the short-run, inventory positions of retailers accelerate in response to upstream supply shocks, consistent with the buffer-stock motive for inventory investment, although, inventory investment behavior reverts to zero a few months after the shock's origination. Sales growth on the other hand decelerates rapidly. Cumulatively, we see that supply chain shocks of this nature have a permanent, albeit small, effect on inventory holdings at retailers, while sales levels are mostly unresponsive. The long-run responses to these shocks perhaps explain some of the puzzle related to the high inventory-to-sales ratio present at the retail level that is persistent through the present day (1.47 on average over our sample period).

In essence, upstream disturbances felt by manufacturers amplify in effect at the retailer level, leading to higher levels of precautionary inventory investment above-and-beyond realized demand, which is consistent given differences in inventory turnover between these two sectors (Kesavan et al., 2016). This finding is consistent with the "bullwhip effect" or demand amplification phenomenon discussed in supply chain and operations research fields (Metters, 1997; Let et al., 1997; Bray & Mendelson, 2013).

Beyond these responses, we can also approximate the response of retailer production levels to $\widehat{u_t}$ shocks by leveraging the following identity: $Q_t = S_t + \Delta H_t$, which implies current period firm production consists of sales (demand), and newly created inventories. Using this identity, we can approximate production responses by adding the point estimates of inventory investment's transitory response to a $\widehat{u_t}$ shock with the cumulative level response of sales to a $\widehat{u_t}$ shock. Figure 6 depicts this production response with 90% bootstrapped confidence intervals.

FIGURE 6
RESPONSES OF RETAILER PRODUCTION TO A $\widehat{u_t}$ SHOCK

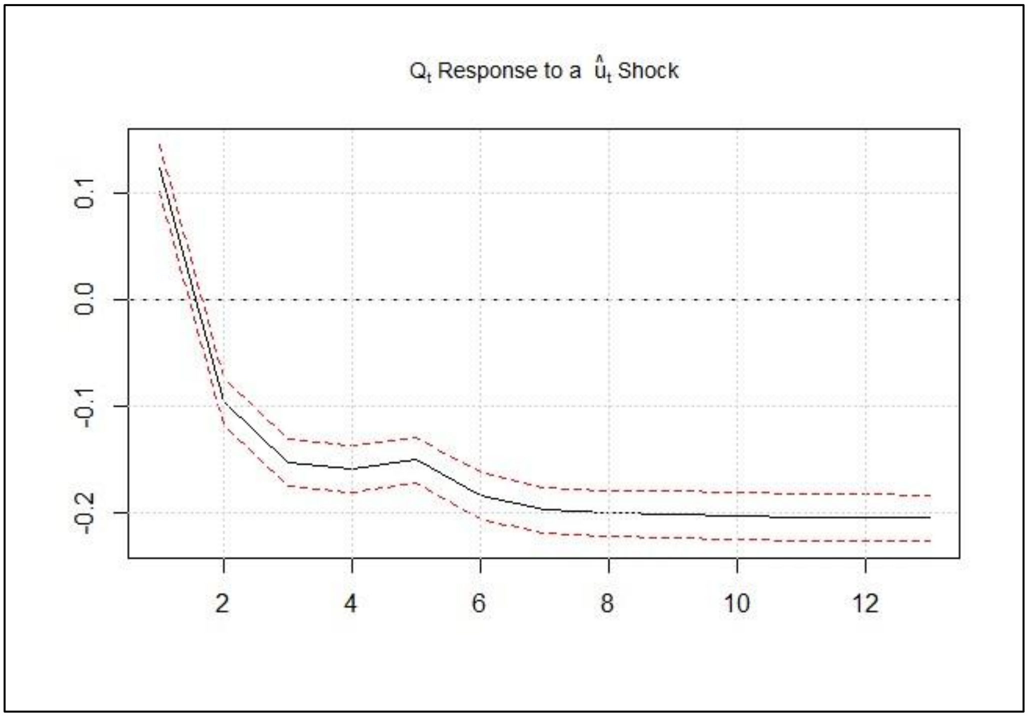


Figure 6 shows an intriguing result. Retail production falls severely, and permanently in response to upstream shocks. In essence, under supplier stress, retailers experience a permanent level-shift in their production that is difficult to recover from in the short-run. The implication of such a result coupled with our previous responses suggests that retailers require some degree of insulation from upstream shocks to preserve their long-run output levels and minimize excess inventory investment.

These results are most consistent with *Scenario 2*, but with a twist. While the nature of our identified shock implies that upstream firms are producing H_t levels less than H_t^*, leading to long-run retailer underproduction, there is an initial swell or transference of inventories to retailers almost immediately in response to said shock. Retailer behavior is such that inventories in the pipeline are accumulated quickly, and then burned down in the form of sales. Cumulatively, however, future period inventory investment tends towards excessive levels, while sales growth returns to its steady state. The implication herein is lost sales are more costly downstream compared to the direct carrying costs leading to retailer inventory-hoarding as a precautionary measure to buffer against upstream underperformance or shocks to upstream performance.

CONCLUDING REMARKS

Overall, this paper contributes to the existing body of research related to global value chains, and inventories by shedding light on the transmission mechanisms of upstream manufacturing shocks to downstream retailers. While previous studies have extensively formalized the linkages between different stages of the supply chain, the lack of a comprehensive exposition on the effects of manufacturing shocks on retailers' inventory investment, sales growth, and production has left a crucial gap in understanding the long-run implications of upstream supply chain shocks on downstream economic agents. Through a rigorous two-step procedure employing reduced-form semiparametric smooth coefficient model, and a structural vector autoregressive model, we identify and quantify the repercussions of supply chain disturbances in the retail sector using monthly data spanning from January 1999 to December 2021.

Our findings reveal a significant, and lasting impact of manufacturing supply chain shocks on downstream retailers, wherein the excess accumulation of inventories results in a long-run level-shift following a unit supply chain shock, accompanied by a short-term decline, and subsequent stabilization in demand. This dynamic is indicative of the high inventory-to-sales ratio prevalent in the retail sector. Furthermore, this study draws attention to the considerable and permanent decrease in retailer output post-shock, underscoring the enduring consequences of disruptions in the manufacturing supply chain on the downstream retail sector.

At the outset, we partially motivated our study as an opportunity to provide some structural context to the mechanisms driving supply chain shocks felt at the retailer-level. By leveraging a parsimonious, albeit stylized, flexible accelerator model, we generate simulation results for a manufacturing supply chain shock that produces results consistent with known supply chain phenomena. Shocks at the manufacturer level are structurally distorting firm costs, making minimization arduous and inconsistent, thus, the reverberation of these shocks should be felt similarly—if not, at a greater magnitude—by retailers in the same industry. In essence, if manufacturers are far off from their H_t^* target because of some supply chain shock, the proportion of inventories retailers will subsequently target downstream will also be accordingly distorted. In our setting, a unit supply chain shock leads to both inventories hoarding and a transitory loss in sales.

This loss can be explained by the lead time necessary to accumulate inventories. In the short-run, retailers cannot service realized demand leading to backlogged sales, and a transitory dip in demand, however, a natural response to this would be to increase one's buffer-stock or target inventory levels altogether to minimize the probability of future backlogs in the long-run. As inventories accumulate, sales return to normal, but retailers now experience a permanent level-shift in their long-run inventory positions. As retailers build up excess inventories, their long-run production of new output falls as there is more stock to fall back on. By extension, the relatively high inventory-to-sales ratio in the data is expressive of firm buffer-stock motives according to our results.

From a welfare standpoint, our model and simulation results imply that supply chain shocks viewed through the lens of inventories leave consumers worse off in the short-run, as inventory levels fall across the value chain, but in the long-run leave retailers in a considerably less-productive, and more costly state, as they reduce their permanent levels of production, while also carrying considerably higher levels of inventory units, which bear direct monetary consequences. Behaviorally, our model implies retailers are making this decision to avoid backlogging sales or losing sales altogether.

From a policy standpoint, regulators and government agencies would do well to account for H_t^* when designing policies to insulate industries, particularly those operating downstream, from supply chain shocks. If target inventory levels are too low at the manufacturer level, such a shock reverberates strongly, and permanently downstream. From a macroeconomic standpoint, nations in theory could establish national inventory targets that can differ from industry targets and then subsidize the difference between the inventory investment necessary to be fully insulated from supply chain shocks and the potentially lower levels of inventory investment that firms or industries make to cost-minimize. A more formal model expanding on this dynamic is best left for future work, however.

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