Spread Too Thin: The Impact of Lean Inventories*

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Abstract

Widespread adoption of just-in-time (JIT) production has reduced inventory holdings. This paper quantifies a tradeoff created by JIT between firm profitability and vulnerability to supply disruptions. Empirically, JIT adopters experience higher sales and less volatility on average while also exhibiting heightened sensitivity to aggregate supply conditions and weather events faced by their suppliers. I explain these facts in a structurally estimated general equilibrium model of JIT production. Relative to a counterfactual economy reflecting the 1970s and 1980s, the baseline model implies an 8.8% increase in firm profits in normal times but a substantially deeper contraction amid a supply disruption.

Keywords: Inventory investment. Firm dynamics. Just-in-time production.
JEL Codes: D22, D25, E22, E23, G31

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1 Introduction

Up to 70% of manufacturers have reportedly adopted just-in-time (JIT) production, a management philosophy that aims to minimize the time between orders.[1] Firms adopt JIT in an effort to cut costs associated with managing large material purchases and storing idle stocks. Instead, these firms commit to placing smaller more frequent orders from suppliers.[2] Consequently, lean inventory management has contributed to the approximately 20% decline in the aggregate inventory-to-sales ratio since 1970.[3]

Do improvements in inventory management matter for macroeconomic fluctuations? Theoretically, in general equilibrium, inventories have been found to be immaterial for aggregate dynamics (Khan and Thomas, 2007; Iacoviello et al., 2011). Empirically, some find that inventory management improvements decreased aggregate volatility (Davis and Kahn, 2008) while others (Stock and Watson, 2002) find that it was broadly inconsequential.

This paper offers a new perspective on the role of lean inventories in driving aggregate fluctuations, finding that it can create macroeconomic fragility in the face of unexpected supply disruptions such as those experienced from the onset of COVID-19. I document evidence of a tradeoff from a novel dataset of JIT firms and quantitatively assess the role that lean production plays at the aggregate level in a structurally estimated heterogeneous firms model.

I first provide firm-level evidence linking the JIT adoption decision to higher firm sales and lower firm volatility. This provides motivating evidence as well as a set of moments that I use when structurally estimating the model. Within firms, JIT adoption is associated with a 13% decrease in inventory-to-sales ratios, a 9% increase in sales, and a 7.5% increase in sales per worker. In addition, JIT firms experience a 17% and 23% decline in sales and employment growth volatility, respectively. These empirical results, though not causal, are consistent with positive selection into

[1] In 2015, the Compensation Data Manufacturing & Distribution Survey found that 71% of surveyed firms employ lean manufacturing. Similarly, in 2007, the Industry Week/MPI Census of Manufacturers found that 70% of respondents had implemented lean manufacturing.

[2] Ohno (1988) provides a detailed history of JIT which started with Toyota's Kanban system.

[3] U.S. Bureau of Economic Analysis, Ratios of nonfarm inventories to final sales of domestic business [A812RC2Q027SBEA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/A812RC2Q027SBEA.

JIT which subsequently yields firm-level efficiency gains as in my model.

I then exploit variation external to the firm and document that JIT adopters are more exposed to supply disruptions as proxied by fluctuations in aggregate unfilled orders. At the firm level, sales among JIT firms decline more strongly than their non-JIT counterparts when there is an increase in the economy-wide level of unfilled orders. JIT firms are estimated to be 30% to 50% more sensitive than non-JIT firms. In addition, JIT adopters experience a 6.6% to 8.6% sharper drop in sales and employment when their suppliers are faced with adverse weather events. My analysis points to heightened sensitivity among JIT firms upon the realization of external supply shocks, indicating that an economy composed of more JIT producers is less resilient to such disturbances.

In light of these empirical facts, I build and structurally estimate a dynamic general equilibrium model of JIT production. The model features a distribution of firms that differ in idiosyncratic productivity, inventory holdings, and inventory management strategy. Materials, needed for production, can be acquired subject to a stochastic fixed order cost. JIT firms draw order costs from a distribution that is first order stochastically dominated by those of non-JIT firms. Implementing JIT requires incurring an initial adoption cost and a smaller continuation cost thereafter. In a given period, firms must choose their JIT status, how much to order, and how much to produce.

I numerically solve and structurally estimate my baseline model via the simulated method of moments (SMM) using data from 1990 to 2019. Relative to a counterfactual economy estimated using data from 1971 to 1989, the baseline model yields a welfare gain of 0.38%. In addition, the baseline model delivers an 8.8% increase in firm profits and a 3.7% increase in measured TFP in the steady state. Intuitively, JIT adoption leads to a reduction in fixed order costs which enables adopters to better align their material input usage with realized productivity. As a result, measured aggregate productivity rises as firms smooth out their inventory cycles, yielding a reduction in firm-level volatility, consistent with the micro data.

Whereas individual adopters benefit from JIT in normal times, an economy comprised of more lean producers is more vulnerable to supply disruptions. I model a shock to fixed order costs, calibrated to match the drop in U.S. real GDP during the onset of the COVID-19 pandemic, and find that the baseline economy experiences a decline in output that is more than twice as large as the counterfactual economy. An unexpected spike in fixed order costs causes firms' ordering inaction regions expand at low levels of inventories, leading to a decline in orders which ultimately reduces inventory investment. With fewer material inputs on hand, firm sales also fall. At the aggregate level, the economy therefore experiences both a decline in final sales and inventory investment. These effects are more pronounced in the baseline economy where firms carry fewer stocks to begin with.

Beyond supply disruptions in goods markets, the COVID-19 pandemic also affected labor markets and the demand for services, while prompting fiscal and monetary policy to respond. In this paper, I abstract away from these other features of the pandemic and focus on supply disruptions in an economy with heterogeneity in inventory management practices. To this end, I next consider a broader supply disruption in which fixed and marginal order costs spike. In this scenario, the baseline economy continues to experience a deeper crisis amid the supply disruption, though I find that the baseline economy is particularly vulnerable to shocks to fixed ordering costs.

In short, my empirical and theoretical analysis quantifies a stark tradeoff between long-run gains and macroeconomic vulnerability to supply disruptions. Firms benefit in normal times from pursuing a lean inventory strategy, however upon the realization of an unanticipated supply disruption, an economy populated by more JIT firms experiences a deeper crisis than one with fewer lean producers.

Inventory investment has long been of interest as a potential source of macroeconomic volatility.[4] Seminal contributions developed production smoothing models (Ramey and Vine, 2004; Eichenbaum, 1984), stock out avoidance models (Kahn, 1987), and (S,s) models (Scarf, 1960; Caplin, 1985) of inventory investment. Khan and Thomas (2007) elegantly models inventories in general equilibrium and finds that they play little to no role in amplifying or dampening business cycles.[5] My model is similar though I introduce an endogenous JIT adoption decision and analyze

[4] See for instance Ahmed et al. (2004), McConnell and Perez-Quiros (2000), McCarthy and Zakrajsek (2007), Irvine and Schuh (2005), and McMahon and Wanengkirtyo (2015).

[5] Iacoviello et al. (2011) comes to a similar conclusion through a different model. On the other hand, Wen (2011) builds a stock out avoidance model and finds that inventories can stabilize aggregate fluctuations.

an unexpected shock to fixed order costs rather than a productivity shock under aggregate uncertainty. The shock that I study reflects disruptions associated with order delays and is most closely related to Alessandria et al. (2023), which finds that the aggregate effects of shipping delays are stronger when inventories are at low levels, consistent with my results.

This paper also speaks to the management literature that focuses on assessing the gains to JIT. Kinney and Wempe (2002) finds that JIT adopters outperform non-adopters, primarily through profit margins.[6] Gao (2018) examines the role of JIT production in corporate cash hoarding. My paper provides a bridge between evidence documented in the management literature and the rich literature on inventories in macroeconomics by highlighting how JIT production can matter for aggregate outcomes.

Furthermore, this paper relates to the literature on supply chain disruptions. On the empirical front, I adopt a strategy similar to Barrot and Sauvagnat (2016) to determine whether JIT producers are disproportionately exposed to unexpected weather events. Other empirical work has assessed how shocks propagate through a network of firms.[7] Similarly, Cachon et al. (2007) assesses empirical evidence of the bullwhip effect along the supply chain. From a theoretical perspective, my paper relates to models of heterogeneous firms, sunk costs, and supply chains. As previously noted, Alessandria et al. (2023) study delays in a general equilibrium model with input-output linkages. Furthermore, Meier (2020) models supply chain disruptions in the context of time to build. My paper explicitly links supply disruptions to an important source of investment at the aggregate level, inventory accumulation.

The rest of the paper is organized as follows. Section 2 documents evidence that is consistent with the stabilizing effects of JIT at the firm level along with the exposure to unexpected shocks that it engenders at the macro level. Sections 3 and 4 develop the general equilibrium model of lean production. I estimate the model in Section 5. Section 6 quantifies the aforementioned micro-macro tradeoff associated with JIT, and Section 7 concludes.

[6]Nakamura et al. (1998) as well as Roumiantsev and Netessine (2008) find similar evidence.

[7]For instance, Carvalho et al. (2021) does this in the context of the 2011 Japanese earthquake.

2 Empirical Patterns Among JIT Firms

I first document empirical evidence indicating that JIT adopters are more efficient and yet more exposed to supply disruptions. I use this as motivating evidence for the model outlined in Section 3. This analysis will also provide moments and external validation to the model once I structurally estimate it.

I develop a new measure of JIT adoption among publicly traded manufacturers by updating and extending previous work in the literature (Kinney and Wempe, 2002; Gao, 2018). This is done through an exhaustive analysis of news reports and SEC filings. Following the literature, I search these documents for key words such as "JIT," "just-in-time," "lean manufacturing," "pull system," and "zero inventory." I then analyze each of these documents to confirm the year of adoption and to ensure that the firm in question implements JIT rather than any suppliers potentially also mentioned in the announcements. In all, my dataset identifies the years in which approximately 185 Compustat manufacturers adopted JIT.

The data on JIT adoption could be subject to measurement error. First, there are potentially false negatives in the cross-section (i.e., JIT firms that are erroneously labeled as non-JIT firms). I account for this possibility when modeling JIT by introducing a parameter to my structural model that allows the observed frequency of adoption to differ from the true frequency of adoption. Section 5 discusses this in further detail. Second, there could be measurement error in the reported years of JIT adoption. Appendix A validates my measure of JIT through an event study approach by demonstrating that inventory holdings begin to decline precisely in the recorded year of adoption.

My final sample consists of an unbalanced panel of about 2,500 unique manufacturing firms spanning the years 1971 to 2019. Appendix A provides summary statistics of the data, and it also corroborates the empirical results using an alternative measure of JIT based on declines in historical inventory-to-sales ratios within narrowly defined industries.

I merge my measure of JIT adoption with firm-level balance sheet information from Compustat Fundamentals Annual data over the aforementioned years. To complete certain exercises in this section, I merge these data with additional information such as the Census M3 Survey and county-

Table 1: JIT Adoption and Firm Performance

	Inventory-to-sales	Sales	Sales per worker
JIT	-0.131**	0.094***	0.075**
	(0.059)	(0.030)	(0.032)
Fixed effects	Firm, Sector × Year	Firm, Sector × Year	Firm, Sector × Year
Firms	2,252	2,252	2,252
Observations	20,216	20,216	20,216

Note: The table reports panel regression results based on regression (1). The dependent variables are log inventory-to-sales, log sales, and log sales per worker. Lags of log employment, log capital stock, and log order backlogs are specified as controls. Two-digit SIC codes are specified in the sector-by-year fixed effects. Standard errors are double clustered along the firm and fiscal year levels. The standard deviations of the dependent variables are 0.80, 2.18, and 0.89, respectively. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

level weather events from the National Oceanic and Atmospheric Administration (NOAA).

Using these data, I document four sets of facts about JIT adopters. First, JIT adoption is associated with lower inventory holdings, higher sales, and higher sales per worker.[8] I estimate regressions of the following form:

$$y_{ijt} = \gamma \text{JIT}_{ijt} + \mathbf{X}'_{ijt}\beta + \delta_{jt} + \delta_i + \nu_{ijt}, \tag{1}$$

where y_{ijt} is an outcome variable for firm i belonging to sector j in year t. The regressor of interest, JIT_{ijt}, is a time-varying indicator for whether a firm is a JIT adopter in a given year. I specify firm and sector-by-year fixed effects in these regressions. In addition, I control for lagged firm employment, capital stock, and order backlogs.[9]

Table 1 reports the regression results. The first column implies that JIT adopters experience a roughly 13% decline in their inventory-to-sales ratios following adoption.[10] The final two columns show that following adoption, firms experience a 9% increase in sales and a 7.5% increase in sales per worker, the latter of which is a proxy for firm-level productivity. The results imply changes of

[8] This is consistent with Fullerton and McWatters (2001) and Cua et al. (2001).

[9] Having more outstanding orders (observed through higher order backlogs) today can generate higher sales in the future, once the orders are fulfilled. To account for this, I include a lag of firms' observed order backlogs in the set of controls.

[10] These estimates are consistent with the results in Figure A1 which takes an event study approach to estimate the effect of JIT adoption on the inventory-to-sales ratio within the firm.

Table 2: JIT Adoption and Firm Volatility

	Sales growth	Employment growth
JIT	-0.174**	-0.233***
	(0.066)	(0.063)
Fixed effects	Sector × Year	Sector × Year
Firms	1,290	1,290
Observations	8,483	8,483

Note: The table reports panel regression results based on regression (2). The dependent variables are rolling five-year standard deviations of firm sales growth and employment growth. Lagged log capital stock is specified as a control. Two-digit SIC codes are specified in the sector-by-year fixed effects. Standard errors are double clustered along the firm and fiscal year levels. The standard deviations of the dependent variables are 0.73, and 0.75, respectively. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

16%, 4%, and 8% of one standard deviation in the outcomes, respectively. The regression results allude to the benefits of JIT in my model. Facing lower fixed order costs, adopters hold fewer inventories in favor of placing smaller more frequent orders. Upon shrinking their inventory stocks, adopters also incur fewer carrying costs. These cost reductions enable JIT firms to allocate more resources to production, allowing them to generate more sales. As a result, these coefficients reflect both selection and treatment effects.

Second, JIT adopters experience less micro volatility. I estimate the following regression:

$$y_{ijt} = \gamma \text{JIT}_{ijt} + \mathbf{X}'_{ijt}\beta + \delta_{jt} + \eta_{ijt}, \tag{2}$$

where y_{ijt} now denotes rolling 5-year standard deviations of sales growth or employment growth for firm i in sector j in year t. Table 2 reports the results. Adopters see a roughly 17% to 23% decline in sales growth and employment growth volatility. This is consistent with the stabilizing role that JIT plays in the model. Due to the lower fixed ordering costs, firms are able to more easily time their orders and can smooth out their inventory cycles which moderates the variability of other outcomes as well.

I next document facts relating to firm-level exposure brought on by JIT, exploiting aggregate

Table 3: JIT Adoption and Aggregate Unfilled Orders

	(1)	(2)
Log unfilled orders-to-new orders	-0.161**	
	(0.078)	
Log unfilled orders-to-new orders × JIT	-0.076***	-0.049***
	(0.019)	(0.016)
Fixed effects	Firm	Firm, Sector × Year
Firms	2,261	2,252
Observations	20,294	20,216

Note: The table reports panel regression results from regression (3). The dependent variable is the log of firm sales. Lagged firm capital stock, firm employment, firm order backlog, aggregate new orders, and contemporaneous JIT adoption indicator are specified as controls. Two-digit SIC codes are specified in the sector-by-year fixed effects. Standard errors are double clustered along the firm and fiscal year levels. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

variation and examining sensitivity to aggregate supply conditions and weather events. The regression results accord with the model in that adopters are less insured against unanticipated supply disruptions, and an economy with more JIT firms is more exposed to such events.

Third, JIT adopters tend to be more sensitive to aggregate supply fluctuations. I merge my data with aggregate data from the Census M3 survey and estimate regressions that interact adoption with unfilled orders (i.e., order backlogs). Unfilled orders spiked following the onset of COVID-19 as supply bottlenecks and other disruptions led to widespread delays in order fulfillment. If JIT firms are more sensitive to supply disruptions, then we should observe more adverse outcomes for these firms relative to non-JIT producers when aggregate unfilled orders rise. I therefore run the following regression:

$$y_{ijt} = \gamma_1 \text{JIT}_{ijt} + \gamma_2 \text{UnfilledOrders}_t + \gamma_3 \big[\text{JIT}_{ijt} \times \text{UnfilledOrders}_t\big] + \mathbf{X}'_{ijt}\beta + \text{FE} + \varepsilon_{ijt}, \tag{3}$$

Because unfilled orders can rise due to higher demand rather than supply constraints (i.e., through a rise in new orders), I specify the ratio unfilled orders-to-new orders in my regressions rather than the level of unfilled orders.[11] The coefficient γ_3 therefore measures the extent to which JIT firms exhibit more or less sensitivity to increases in unfilled orders relative to new orders.

Table 3 reports the regression results. Based on column (1), a 1% increase in the ratio unfilled orders to new orders is associated with a roughly 0.16% decrease in sales among non-adopters. Adopters experience an additional sales decline of 0.08% beyond this baseline. Turning to column (2), when controlling for sector-by-year fixed effects, which subsumes the second term of equation (3), I find that the magnitude of the excess sensitivity of JIT firms is similar, implying that JIT firm sales decline by about 0.05% more than non-JIT firms. These estimates suggest that JIT firms are roughly 30% to 50% more sensitive than non-JIT firms.

Finally, JIT adopters are more sensitive to weather events faced by their suppliers. I examine this by merging my data with county-level weather events from NOAA using the Compustat Segment Files and links from Barrot and Sauvagnat (2016). I then estimate the following regression:

$$y_{ist} = \psi_1 \text{JIT}_{it} + \psi_2 \text{WeatherEvent}_{st} + \psi_3 \big[\text{JIT}_{it} \times \text{WeatherEvent}_{st}\big] + \mathbf{X}'_{ist}\beta + \text{FE} + \omega_{ist}. \qquad (4)$$

The "WeatherEvent" regressor is an indicator for a weather event occurring in the zip code where supplier s is headquartered in a given year. I collect information on county-level weather events from NOAA and link these events to public firm headquarter zip codes via the aforementioned Barrot and Sauvagnat (2016) links.

Ideally, one would want to link upstream weather events to the zip codes in which suppliers' production takes place. The Compustat data is limited in this respect since once cannot necessarily assume that production occurs at or near a firm's headquarters. Nonetheless, weather events may disrupt other operations which might take place at a firm's headquarters such as logistics. Overall, I regard this data limitation as a form of measurement error which likely biases my estimates toward zero.

Table 4 provides four sets of results. The first two columns report the effect of a weather event

[11] This is motivated by the definition of unfilled orders: $\text{Unfilled orders}_t = \text{Unfilled orders}_{t-1} - \text{Shipments}_t + \text{New Orders}_t$.

Table 4: JIT Adoption and Weather Events

	Sales		Employment	
	(1)	(2)	(3)	(4)
Weather event	0.019		0.009	
	(0.013)		(0.013)	
Weather event × JIT	-0.025	-0.086***	-0.014	-0.066*
	(0.020)	(0.030)	(0.020)	(0.036)
Fixed effects	Firm, Supplier, Year	Firm, Supplier×Year	Firm, Supplier, Year	Firm, Supplier×Year
Firms	349	172	349	172
Observations	4003	1214	4003	1214

Note: The table reports panel regression results based on regression (4). The dependent variables are log sales and log employment. Finished goods inventory is specified as a control variable. Standard errors are double clustered at the customer-supplier level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

on sales while the latter two columns report the effect on employment. The point estimates on the interaction between a supplier weather event and a JIT customer are negative across all specifications, and are statistically significant when controlling for supplier-by-year fixed effects. The latter estimates, reported in columns (2) and (4), control for upstream time-variation which includes year-specific supplier characteristics such as age and size, as well as other unobserved shocks that suppliers face in a given year. Given the more robust set of controls specified in these regressions, columns (2) and (4) reflect my preferred specification.

Through the series of links required to estimate these regressions, the sample size is reduced considerably.[12] Nonetheless, in my preferred specification, I find that on average a supplier weather event in my sample predicts an additional 6.6% to 8.6% decline in JIT firm sales and employment relative to non-JIT firms.

Taken together, the data suggest that JIT adopters benefit from more sales and smoother outcomes. At the same time, adoption is associated with heightened exposure to aggregate supply conditions and supply disruptions as proxied by local weather events. My model of heterogeneous firms with inventories, fixed ordering costs, and an endogenous JIT adoption decision can explain these

[12]Building this sample requires linking weather events to firm (supplier) headquarters in Compustat, then linking these suppliers to their customers (through the Segment files), and finally linking the customers to their JIT adoption status.

patterns. The model also allows me to quantitatively assess the impact of JIT amid an unanticipated aggregate supply disruption, something that cannot be easily captured by firm level regressions.

3 A Model of Just-in-Time Production

Having illustrated the essence of the tradeoff in the data, I next build the full general equilibrium model which will provide quantitative statements about the implications of JIT. The model is similar in spirit to Khan and Thomas (2007) and Alessandria and Choi (2007).

A representative household has preferences over consumption and leisure. The household supplies its labor frictionlessly to the two sectors of the economy: the intermediate goods sector and the final goods sector. A representative intermediate goods firm produces materials by using labor and capital. In addition, a continuum of heterogeneous final goods firms make use of labor and materials to produce using a decreasing returns to scale technology. Final goods producers are heterogeneous in idiosyncratic productivity, inventory stocks, and JIT adoption status. All markets are perfectly competitive.

The representative household is endowed with one unit of time in each period and values consumption and leisure according to the following preferences:[13]

$$U(C_t, H_t) = \log(C_t) + \phi(1 - H_t),$$

where $\phi > 0$ denotes the household's labor disutility. Total hours worked is denoted by H_t and labor is paid wage, w_t. In addition to wage income, the household earns a dividend each period from ownership of firms, D_t, and chooses savings on a one period riskless bond, B_{t+1}, given interest rate R_{t+1}. The representative household, facing no aggregate uncertainty, maximizes its utility:

$$\max_{C_t, H_t, B_{t+1}} \sum_{t=0}^{\infty} \beta^t U(C_t, H_t),$$

[13] Rogerson (1988) microfounds these preferences in a model of indivisible labor and lotteries.

subject to its budget constraint which holds for all t,

$$C_t + B_{t+1} \leqslant R_t B_t + w_t H_t + D_t.$$

The parameter $\beta \in (0, 1)$ is the household's subjective discount factor.

The representative intermediate goods firm produces materials using capital K_t and labor L_t according to:

$$F(K_t, L_t) = K_t^{\alpha} L_t^{1-\alpha}.$$

Taking prices as given, the problem of the intermediate goods firm is:

$$\max_{K_t, L_t} q_t F(K_t, L_t) - w_t L_t - R_t K_t,$$

where q_t denotes the price of the intermediate good.

Finally, a continuum of final goods firms produce using materials, m_t, and labor, n_t, according a decreasing returns to scale technology:

$$y_t = z_t m_t^{\theta_m} n_t^{\theta_n}, \quad \theta_n + \theta_m < 1,$$

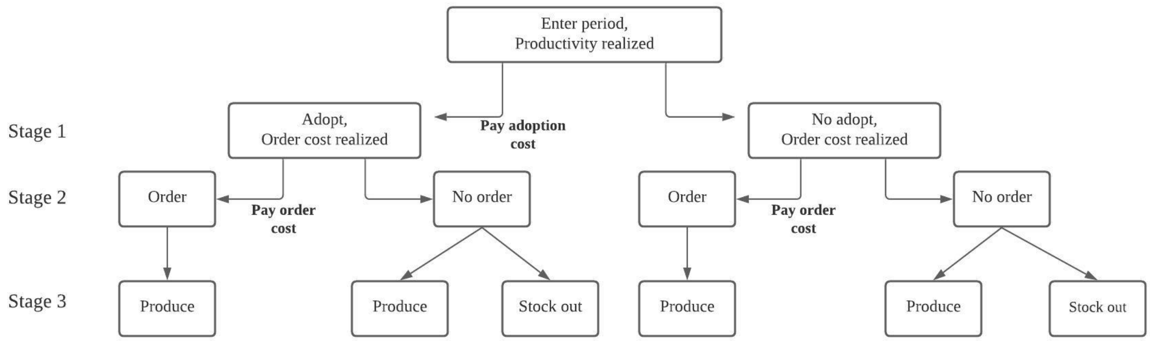
where idiosyncratic productivity evolves as an AR(1) in logs:

$$\log(z_{t+1}) = \rho_z \log(z_t) + \sigma_z \varepsilon_t, \quad \varepsilon_t \sim N(0, 1).$$

Materials are drawn from the firm's existing inventory stock, s_t, to use in production. Final goods firms procure new materials from the intermediate goods firm subject to a stochastic fixed order cost drawn from a known distribution.

Figure 1 details the final goods producers' decision-making timeline. Each period is broken into three stages. A producer enters the period with realized productivity, z_t, inventory stock, s_t, and adoption status, a_t. In the first stage, the producer decides whether or not to adopt JIT. If a

Figure 1: Decisions of Final Goods Firms



Note: The figure summarizes the order of the decisions made by final goods firms within a period.

producer does not enter the period as a continuing adopter, it must pay c_s in order to initially adopt. Alternatively, if the producer enters the period as an adopter, it must pay a smaller continuation cost $0 < c_f < c_s$ in order to maintain its status as a JIT producer.

Intuitively, adopting JIT requires that a plant repurpose its shop floor, enter into long-term contracts with suppliers to fulfill orders in a timely fashion, and possibly even purchase new technologies to facilitate information sharing with suppliers. The sunk setup cost encompasses all of these one-time costs. The continuation cost embodies smaller costs for suppliers to participate in timely delivery, costs of training labor on JIT best practices, and greater attention or communication required to share information with suppliers.

In the next stage, producers learn their order costs, $\xi \sim F(\xi)$, and decide whether or not to place an order, o_t. JIT producers face a more favorable order cost distribution, $\mathbb{E}(\xi_A) \leqslant \mathbb{E}(\xi_{NA})$. Lastly, following the adoption and the order decisions, final goods producers decide how much to produce.

I characterize the final goods firms' problem in terms of inventory stocks rather than specific order or material input choices. In particular, if a firm enters the period with inventory stock s_t, its target inventory stock is denoted by s_t^*. This means that any orders, if placed, are defined as $o_t = s_t^* - s_t$. Following the order decision, suppose that inventory stock $\widetilde{s}_t$ is carried into the production stage.[14] Materials used in production are then defined as $m_t = \widetilde{s}_t - s_{t+1}$ where s_{t+1} refers to the inventory stock carried forward into the next period. In what follows, I suppress the time subscript and instead denote next period variables with a prime.

Stage 1: Adoption Decision

A final goods producer begins the period with (z, s, a), faces labor-denominated adoption costs $\{c_s, c_f\}$, and endogenous prices, p, q, and w. The firm first decides whether to adopt JIT. Note that the adoption status is a binary outcome. The value of adopting is:

$$V^A(z,s,a) = \max\left\{ -pwc(a) + \int V^O(z,s,1,\xi)dF(\xi_A), \int V^O(z,s,0,\xi)dF(\xi_{NA})\right\}, \tag{5}$$

where

$$c(a) = \begin{cases} c_s & \text{if no JIT } (a=0) \\ c_f & \text{if JIT } (a=1), \end{cases}$$

and $V^O(z,s,a,\xi)$ refers to the firm's value in the second stage. Order costs are assumed to be distributed uniformly: $F(\xi) = U(\underline{\xi}, \overline{\xi})$.[15] The firm's optimal adoption policy, $a'(z,s,a)$, solves (5).

Stage 2: Order Decision

Given the firm's order cost draw, ξ, also denominated in units of labor, it then decides whether to place an order, o. If the firm is an adopter, its order cost distribution is first order stochastically dominated by those of non-adopters. The value in the second stage is

$$V^O(z,s,a,\xi) = \max\left\{ -pw\xi + pqs + V^*(z,s,a), V^P(z,s,a)\right\}, \tag{6}$$

[14] $\widetilde{s} = s$ if no order is placed and $\widetilde{s} = s^*$ if an order is placed.

[15] As in Khan and Thomas (2007), I assume uniformly distributed order costs. In this context, uniformly distributed order costs are appealing because they strengthen the firms' precautionary inventory holding motive since order costs are not clustered around a central region as with, for instance, a normal distribution. To the extent that my later results expose a vulnerability associated with firms carrying too few inventories, this assumption should be relatively conservative.

where the value of placing an order is[16]

$$V^*(z,s,a) = \max_{s^* \geqslant s} \Big[-pq(s^*-s) + V^P(z,s^*,a) \Big], \tag{7}$$

and $V^P(z,s,a)$ is defined below. The firm's order problem delivers a threshold rule. In particular, a firm places an order if and only if the order cost draw is lower than a threshold order cost: $\xi < \xi^*(z,s,a)$ where

$$\widetilde{\xi}(z,s,a) = \frac{V^*(z,s,a) - V^P(z,s,a)}{pw}, \tag{8}$$

and

$$\xi^*(z,s,a) = \min\big(\max\big(\underline{\xi}, \widetilde{\xi}(z,s,a)\big), \overline{\xi}\big). \tag{9}$$

Stage 3: Production Decision

Upon choosing its JIT status, deciding whether to place an order, and potentially selecting an order size, the firm then makes a production decision. Suppose that a firm enters the production stage with inventory stock $\widetilde{s}$ such that:

$$\widetilde{s} = \begin{cases} s^*\big(z,s,a'(z,s,a)\big) & \text{if order placed} \\ s & \text{if no order placed.} \end{cases}$$

In the production stage, the firm selects labor, $n(z,\widetilde{s},s',a)$, and materials, $(\widetilde{s}-s')$, to maximize profits. Its value function in the production stage is:

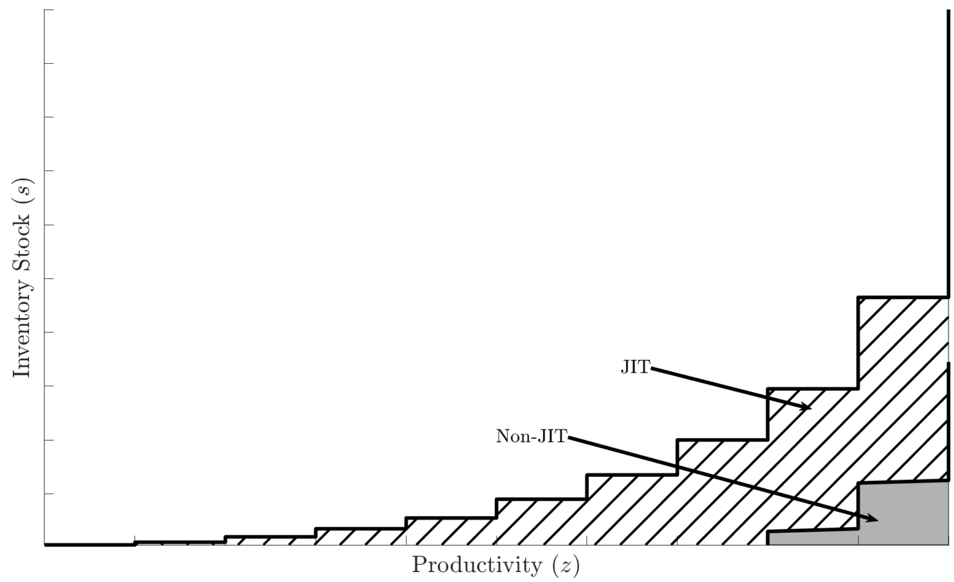
$$V^P(z,\widetilde{s},a) = \max_{s' \in [0,\widetilde{s}]} \pi(z,\widetilde{s},s',a) + \beta \mathbb{E}\big[V^A(z',s',a')\big] \tag{10}$$

where

$$\pi(z,\widetilde{s},s',a) = p\Big[zn(z,\widetilde{s},s',a)^{\theta_n}(\widetilde{s}-s')^{\theta_m} - wn(z,\widetilde{s},s',a) - \frac{c_m}{2}s'^2 \Big] \tag{11}$$

[16] The constraint on the ordering decision allows for only positive orders. In other words, this model abstracts away from inventory liquidation.

Figure 2: Adoption Frontiers



Note: The figure plots the adoption frontier among JIT and non-JIT firms. The solid grey area depicts the region of the state space in which non-JIT firms select into adoption. The striped area and the gray area jointly denote the region of the state space in which existing JIT firms choose to remain adopters.

are period profits. The end of period inventory stock is denoted by s', and c_m is a convex carrying cost of storing unused inventory.[17]

A final goods producer is said to stock out if it enters the period with no inventories, $s = 0$, and chooses to not place an order. Without any inventories, the firm has no material inputs to draw from when making its production decision. As a result, the firm forgoes production in that period. The producer can flexibly restart production in the future conditional on a favorable productivity realization and order cost draw.

4 Analyzing the Model

The endogenous adoption decision allows the model to replicate important features of the data, namely, higher profitability and reduced micro volatility among JIT firms. Since implementing JIT comes at a relatively large sunk cost, not all firms optimally choose to adopt JIT. Figure 2 plots the adoption frontiers for JIT and non-JIT producers. The shaded area in the lower right corner represents the region of the state space in which non-JIT firms choose to adopt JIT. This illustrates the positive selection into adoption implied by the model. Moreover, the scope for initiating adoption is decreasing in inventory stocks as the value of adopting is higher among firms that are closer to their ordering thresholds.

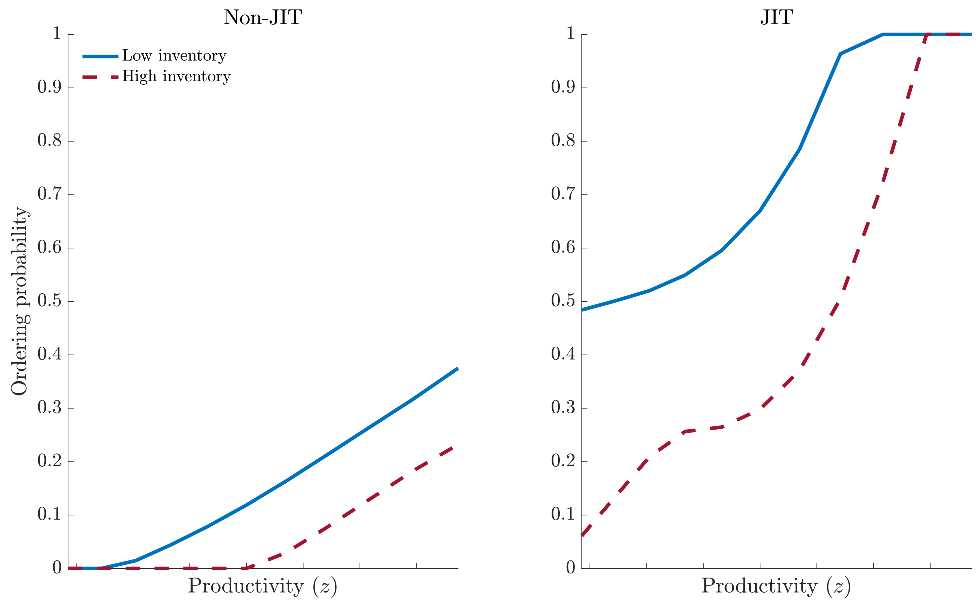
At the same time, a producer is likely to remain an adopter conditional on already being one. This is because the continuation cost of retaining JIT is smaller than the initial sunk cost. Hence, the endogenous adoption decision exhibits persistence. The larger striped area in Figure 2 confirms this intuition. Only the least productive adopters will opt to abandon JIT. Furthermore, the scope for exiting adoption is increasing in inventory holdings. The selection detailed here could contribute to the patterns among JIT firms documented in the data. In particular, the decision to adopt JIT reflects a favorable productivity realization which, when coupled with lower average order costs, leads firms to reduce their inventory stocks and generate more sales such that there is an increase in sales per worker.

Figure 3 shows the probability of placing an order as a function of productivity.[18] Consistent with the decision to select into adoption, order probabilities are increasing in productivity and decreasing in inventory holdings. The benefits of JIT adoption can be understood by comparing the two panels. Across both inventory levels, the probability of placing an order is higher for adopters since they face lower average order costs. Moreover, because JIT producers are able to place more

[17] This quadratic cost specification implies increasing marginal storage costs as in Blinder (1982), Wen (2005), and Luo et al. (2021).

[18] I model the order and delivery of materials differently from Alessandria et al. (2023). Alessandria et al. (2023) features a model with constant fixed ordering costs and uncertainty about whether one's order will be delivered in the current period. If an order is not delivered in the current period, it is delivered with certainty in the next period. Here, as in Khan and Thomas (2007), there is no explicit delay probability. Instead, there is uncertainty with respect to the fixed ordering costs that firms face in a given period, which gives rise to the probabilities of ordering plotted in Figure 3.

Figure 3: Ordering Probabilities



Note: The figure plots the probability of placing an order in the ordering stage as a function of productivity. The left panel plots the probabilities among non-adopters and the right panel plots the probabilities for adopters. The solid blue line reflects a low inventory establishment in the model while the dashed red line reflects a high inventory establishment.

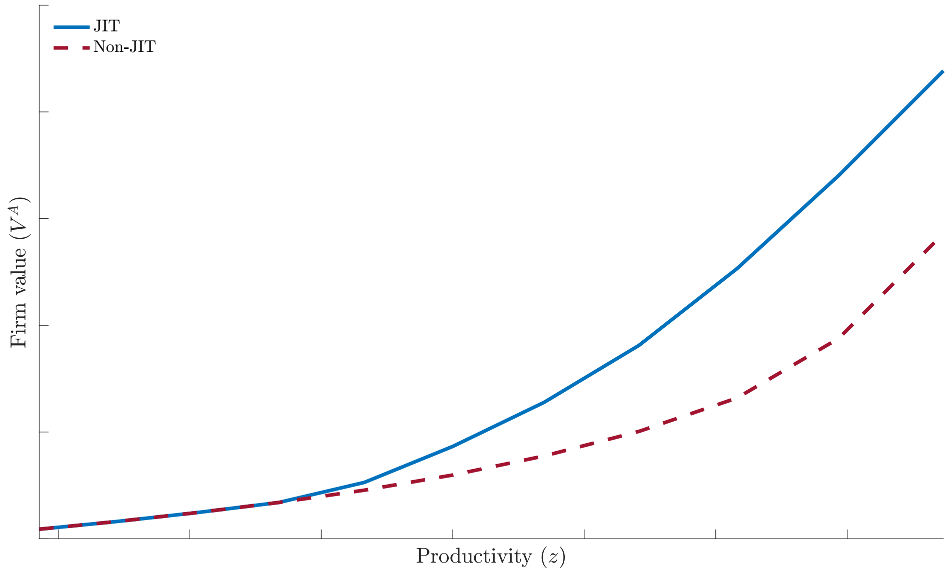
frequent orders, they do not need to carry as many inventories across time. As a result, JIT producer place smaller-sized orders.

Finally, Figure 4 plots the value function for a non-JIT and a JIT producer, holding the inventory stock constant. JIT firms enjoy a higher firm value, $V^A(z, s, a)$, which is increasing in productivity. The two value functions coincide at low levels of productivity where a JIT firm would optimally choose to abandon JIT and become a non-JIT producer, consistent with the frontiers traced out in Figure 2. As productivity increases, the returns to JIT also rise as JIT producers face lower order costs and are able to operate with fewer inventories on hand allowing them to also reduce their storage costs.

5 Structural Estimation

I structurally estimate the model using the micro data analyzed in Section 2. The estimated model captures important features of the firm-level data including the levels of and covariances between

Figure 4: Firm Value



Note: The figure plots the value function for different realizations of idiosyncratic productivity. The solid blue line reflects a JIT producer while the dashed red line reflects a non-JIT producer.

inventories and sales as well as levels and "spikes" in inventory holdings.

The comprehensive search of firm financials and public statements ensures that my data on JIT adoption do not include false positives. However, information on JIT implementation is constrained to what is reported in these records. To allow for the possibility that JIT is more widespread than the observed frequency of adoption in my sample, I use the structure of the model to infer patterns of adoption. As foreshadowed in Section 2, I define a parameter, $\tau \in (0,1)$, that governs the share of observed non-adopters from a simulated panel of firms and calibrate it to match the empirical frequency of adoption.[19]

There are therefore 15 parameters in the model. Aside from the measurement error parameter, τ, I externally fix five parameters to match standard targets in the literature. Table 5 details the annual calibration. The discount factor, β is set to be consistent with a real rate of 4%. The material share, θ_m, is set to match the material share in the NBER-CES database, and the capital share, α, is fixed to match the capital-output ratio. The parameter θ_n is set to match an economy-wide labor share of

[19] As in my sample, a firm in the model is said to be an adopter if at least one of its establishments adopts JIT. Upon simulating a panel of firms, a share τ, are designated non-adopters irrespective of their true adoption status.

Table 5: External Parameterization

Description	Parameter	Value	Notes
Discount Factor	β	0.962	Real rate equal to 4%
Material share	θ_m	0.520	NBER-CES
Capital share	α	0.390	NBER-CES
Labor share	θ_n	0.280	Labor share equal to 0.65
Labor disutility	ϕ	2.550	1/3 of total hours worked

Note: The table reports the five calibrated model parameters.

0.65. The leisure preference is calibrated so that the household works for one-third of total hours.

5.1 Simulated Method of Moments

The parameter vector to be estimated is $\theta = \begin{pmatrix}\rho_z & \sigma_z & \underline{\xi}_{NA} & \overline{\xi}_{NA} & \underline{\xi}_A & \overline{\xi}_A & c_s & c_f & c_m\end{pmatrix}'$. These parameters residing in θ govern the exogenous productivity process, order costs, adoption costs, and the carrying cost. The model has no closed form solution, so I solve it using standard numerical dynamic programming techniques detailed in Appendix B. To parameterize the model, I employ SMM (Duffie and Singleton, 1993; Bazdresch et al., 2018). This is done by computing a set of targeted moments in the model and minimizing the weighted distance between the empirical moments and their model-based analogs.

Specifically, I target 10 moments to estimate the nine parameters. My estimator is therefore an overidentified SMM estimator. Of the ten moments, five are specific to JIT firms and five to non-JIT firms. These five moments, which are the same across both types of firms, are: the mean inventory-to-sales ratio, the covariance matrix of log sales and log inventories (which delivers three moments), and the frequency of positive inventory-to-sales ratio spikes, defined as instances in which the inventory-to-sales ratio exceeds 0.20.[20] I specify the asymptotically efficient weighting matrix which is the inverse of the covariance matrix of the moments.

[20]The empirical moments are listed in Table 7.

5.2 Informativeness of Moments

While the targeted moments jointly determine the parameters to be estimated, there are nonetheless moments that are especially important for pinning down certain parameters. I discuss their informativeness in turn.

Idiosyncratic productivity persistence mostly informs the covariance between log inventory and log sales. At the extreme, as ρ_z approaches one a positive productivity shock that makes a firm profitable enough to flexibly order every period will carry no inventories over time. In this case, sales and inventories would not covary at all. In general, an increase in the persistence of productivity shocks will result in a lower covariance between log inventory and log sales. Moreover, the dispersion of idiosyncratic productivity shocks mostly affects variances.

The order costs are strongly related to the mean inventory-to-sales ratios and variances. An increase in the lower bound of the non-adopter order cost distribution implies higher average order costs which lead to an increase in inventory-to-sales ratios among non-JIT producers. Intuitively, an increase in expected non-JIT order costs raises the returns to adoption. Due to positive selection into adoption, the remaining pool of non-adopters is less productive, meaning that their inventory stocks are higher relative to their sales. Moreover, an increase in the upper support of the order cost distribution for non-adopters raises both the first and second moment of order costs. As a result, an increase in the upper bound will raise the variance of outcomes for non-JIT producers.

On the other hand, an increase in the lower support of the order cost distribution for adopters leads to less dispersion in sales and inventory stocks among JIT producers. This is because an increase in the order cost for adopters will lead some firms along the threshold to switch out of adoption thereby narrowing the range of outcomes among JIT producers in equilibrium. An increase in the upper bound of the order cost distribution for JIT producers will lead adopters to raise their target inventory stocks in an effort to lengthen the time between orders. As a result, inventory-to-sales ratios among existing adopters rise.

An increase in the sunk cost of adoption strengthens the covariance between log sales and log inventories among adopters. To see this note that a higher sunk cost reduces the area representing the adoption frontier for non-JIT producers in Figure 2, but expands the area representing the adoption frontier for current JIT producers. In other words, the conditional probability of remaining an adopter is higher since some JIT firms will find it optimal to maintain their JIT status rather than abandon it and re-incur the higher adoption cost in the future. Hence, the range of outcomes among JIT firms will expand with a higher sunk adoption cost. In contrast to the original set of JIT firms that are relatively more productive and have high sales and low inventories, sales will now be more sensitive to the inventory cycle for some adopters.

On the other hand, the continuation cost of adoption primarily affects moments among non-adopters. A higher continuation cost of adoption reduces likelihood of remaining an adopter conditional on already being one. The marginal producer, which is less productive, will therefore switch out of adoption. As a result, the pool of non-adopters increasingly consists of relatively lean firms which reduces average inventory-to-sales ratios and inventory-to-sales spikes among non-JIT firms.

The storage cost also affects the distribution of inventory-to-sales ratios. A higher storage cost raises the marginal cost of carrying inventories across time, and therefore reduces expected order sizes which reduces the frequency of inventory-to-sales spikes for JIT and non-JIT producers alike.

Figure C1 in Appendix C outlines these key monotonic relationships between the moments and the parameters. In addition, Figure C2 helps assess the sources of identification by reporting the sensitivity of each of the nine parameters to changes in a given moment, based on Andrews et al. (2017). These figures are consistent with the intuition laid out above.

5.3 Estimation Results

I split my sample in two and estimate the model twice, once to fit the moments computed over the years 1990 to 2019, and again to fit the moments computed over the years 1971 to 1989. I define the former as my baseline model, which is intended to reflect present-day patterns in JIT adoption, and the latter as my counterfactual model, which reflects the early days of JIT in the U.S. In what follows, I discuss my baseline model estimation results and report the analogous counterfactual model results in Appendix C.

Table 6: Estimated Baseline Parameters

Description	Parameter	Estimate	Standard error
Productivity shock persistence	ρ_z	0.642	0.0027
Productivity shock dispersion	σ_z	0.044	0.0002
Order cost lower bound (non-JIT)	$\underline{\xi}_{NA}$	0.226	0.0035
Order cost upper bound (non-JIT)	$\overline{\xi}_{NA}$	1.247	0.0130
Order cost lower bound (JIT)	$\underline{\xi}_{A}$	0.063	0.0009
Order cost upper bound (JIT)	$\overline{\xi}_{A}$	0.303	0.0043
Sunk cost of adoption	c_s	0.423	0.0150
Continuation cost of adoption	c_f	0.124	0.0013
Carrying cost	c_m	6.916	0.0042

Note: The table reports the point estimates and standard errors for the nine estimated parameters. Standard errors obtained via numerical differentiation.

Table 6 reports the estimated baseline model parameters, all of which are precisely estimated.[21] The technology parameters, ρ_z and σ_z, are consistent with parameterizations in the literature (Khan and Thomas, 2013; Khan et al., 2020; Hennessy and Whited, 2007).

The lower bound of the order cost distribution among non-JIT producers is 0.226 while the upper support of the order cost distribution among non-adopters is 1.247. On the other hand, I find that order costs among JIT adopters range from 0.063 to 0.303, implying that JIT producers place orders that are about 20% as large as those of non-JIT firms, and indicating a sizable return to adoption for those who can initiate it. The average order costs implied by these estimates amount to 1.3% and 4.9% of value added. Furthermore, the adoption cost estimates suggest a meaningful amount of hysteresis in the adoption decision. In particular, firms pay a continuation cost that is

[21] A test of overidentifying restrictions delivers a J-statistic of 1.96 with a p-value of 0.16 for the baseline model. As a result, I fail to reject that the baseline model is misspecified, lending further support to the validity of my estimates.

Table 7: Baseline Model vs. Empirical Moments

Moment	Model	Data
Mean(inventory-sales ratio$\vert$non-adopter)	0.143	0.141
		(0.002)
Mean(inventory-sales ratio$\vert$adopter)	0.113	0.092
		(0.005)
Std(log sales $\vert$non-adopter)	0.536	0.480
		(0.007)
Corr(log sales, log inventories$\vert$non-adopter)	0.560	0.694
		(0.006)
Std(log inventories$\vert$non-adopter)	0.465	0.514
		(0.007)
Std(log sales $\vert$adopter)	0.405	0.377
		(0.025)
Corr(log sales, log inventories$\vert$adopter)	0.486	0.769
		(0.021)
Std(log inventories$\vert$adopter)	0.450	0.436
		(0.024)
Spike(inventory-sales ratio$\vert$non-adopter)	0.167	0.166
		(0.006)
Spike(inventory-sales ratio$\vert$adopter)	0.026	0.042
		(0.013)

Note: The table reports model-based and empirical moments along with standard errors of the empirical moments.

about one quarter of the original sunk cost. Conditional on being an adopter, the probability of remaining an adopter is 83%. For reference, this estimate is similar though lower than estimates of the sunk cost of exporting, which place the probability of remaining an exporter conditional on already being one at 87% (Alessandria and Choi, 2007). In equilibrium, economy-wide carrying costs are about 3% of value added, a non-negligible amount that prevents firms from storing too many inventories across time.

Table 7 shows that the model is broadly successful in fitting the empirical moments. The model is able to reproduce lower average inventory-to-sales ratios, a lower frequency of spike rates, and less dispersion among JIT firms relative to non-JIT firms. The model does a slightly poorer job of fitting the variance of log sales among JIT and non-JIT producers. This is likely due to the specification of a uniform order cost distribution which generates more dispersion in the length of

Table 8: Empirical and Simulated Regressions

Inventory-to-sales		Sales		Sales growth volatility	
Model	Data	Model	Data	Model	Data
-0.218	-0.215	0.239	0.280	-0.201	-0.172
(0.009)	(0.058)	(0.009)	(0.057)	(0.016)	(0.069)

Note: The table reports model-based and empirical moments with standard deviations and standard errors in parentheses. Empirical coefficients are based on regressions estimated over the years 1990 through 2019.

time between orders that in turn results in greater variability in firm sales.

5.4 Nontargeted Moments

To further assess the baseline model's ability to match the patterns present in the data, I run the empirical regressions reported in Tables 1 and 2 based on a panel of simulated firms from the estimated baseline model. The results are reported in Table 8. For consistency, I report empirical coefficients estimated from 1990 to 2019, the same sub-period over which the baseline model is estimated.[22]

Following adoption, firms in the baseline model reduce their inventory-to-sales ratios by about 22% which is nearly the same as the empirical estimate. At the same time, the model implies that these firms experience a 24% increase in sales, similar to the 28% increase implied by the data. Finally, the baseline model predicts reductions in firm volatility of 20% among JIT firms, close to the 17% and 24% estimated declines in the data.[23] With precisely estimated parameters delivering a broadly successful fit to the data, I can now exploit this structure as a laboratory for quantitative experiments.

[22] Because the model abstracts away from an extensive margin of employment, I do not report model-based estimates for the final column of Table 1.

[23] Because labor demand is modeled as a static and flexible choice, the model-based sales and employment growth volatility regressions deliver the same regression coefficients. As a result, I report only the sales growth volatility regression results in Table 8.

6 Quantifying the Effects of JIT

I proceed to quantify the tradeoff between the long-run gains associated with JIT and the vulnerability to unanticipated supply disruptions that JIT exposes. I first examine the model's steady state to characterize the benefits of lean production. I then analyze the dynamics of the estimated economies following a COVID-19-like supply disruption.

As mentioned in the previous section, I define a counterfactual benchmark model to reflect the JIT adoption patterns of the 1970s and 1980s. Specifically, I re-estimate the baseline model to match the same moments in my sample but computed over the years 1971 to 1989. I re-estimate the order cost distributions and the adoption costs but leave the firm's technology parameters and storage cost parameter fixed at their estimated values according to the baseline model. The reason that I only re-estimate the order costs and adoption costs is because differences in these parameters relative to the baseline estimates will capture the differences in incentives to adopt JIT that are of interest here. For instance, changes in adoption costs from the early sample to the present can reflect new cohorts of managers trained in lean production strategies or changes in information-sharing technologies. In addition, changes to the order cost distributions can reflect changes in delivery costs associated, for instance, with shifts from rail to trucking.

6.1 Long Run Outcomes

A comparison between the two models points to sizable gains associated with JIT adoption. Table 9 reports steady state outcomes in the baseline model relative to the counterfactual economy in percent deviations. The greater prevalence of JIT in the baseline model delivers a 7.8% increase in output and an overall increase in the demand for orders, reflected by a 4.5% increase in the price of orders.

As expected, inventory holdings fall in the baseline model relative to the counterfactual. Relative to the counterfactual, the baseline model delivers a 15% decline in the aggregate inventory-to-sales ratio, close to the observed 23% decline in the ratio of nonfarm inventories to final sales from 1971-1989 to 1990-2019. In addition, profits in the baseline economy rise by 8.8% relative to the

Table 9: Long-Run Aggregates Across Models

Output	Order frequency	Order size	Price of orders
7.75	38.00	-21.16	4.47
Inventory stock	**Profits**	**Measured TFP**	**Welfare**
-7.66	8.82	3.70	0.38

Note: The table reports steady state values of the baseline model relative to the counterfactual model, in percent deviations.

counterfactual.

In the presence of fixed order costs firms optimally hold non-zero inventories. In the baseline model with more JIT adoption, however, a greater number of producers can operate subject to lower order costs. At the aggregate level, this implies that resources are reallocated to high marginal product producers. Because firms place more frequent orders, they enjoy greater flexibility and can better align their material usage with their realized micro productivity realizations. As a result, the baseline model is characterized by a 3.7% increase in measured TFP.

Consumption-equivalent welfare in the baseline model relative to the counterfactual is 0.38%, which is smaller in magnitude than the costs of business cycles (Krusell et al., 2009) and the costs of managerial short-termism (Terry, 2017). These welfare gains would be larger but for the relative increase in the marginal cost of orders in the baseline model due to the increase in order demand. When fixing the price of orders, q, to be the same across the two models, consumption-equivalent welfare gains associated with JIT would almost double.

6.2 Effects of an Unanticipated Supply Disruption

Despite enjoying higher profits and smoother firm-level outcomes, an economy populated by lean producers is more vulnerable to an unexpected supply disruption. To quantify this supply side vulnerability, I consider an unexpected increase in economy-wide fixed order costs and assume that it evolves deterministically according to $\zeta_{t+1} = \rho_{\zeta}^{\xi}\zeta_t$ where $\rho_{\zeta}^{\xi} = 0.50$ and $\zeta_0 > 0$.[24] This shock

[24] Consistent with the literature modeling COVID-19, I model the episode as an unanticipated event (Arellano et al., 2020; Espino et al., 2020). In Appendix D, I show that the results of this exercise are qualitatively unchanged when allowing the shock to be partially anticipated.

shifts the upper support of the fixed order cost distribution of JIT and non-JIT producers:

$$\overline{\xi}_t = \overline{\xi} + \zeta_t.$$

As a result, this shock increases the mean and variance of fixed order costs. An alternative would be to consider only a first moment shock to fixed order cost distributions by imposing the same shock to the lower support. I choose to model a shock that also raises the variance of fixed order costs for two reasons. First, the COVID-19 episode more closely resembles this scenario given the spikes in measured uncertainty observed in 2020. Second, modeling a shock that also raises the variance of fixed order costs allows me to generate a spike in the aggregate inventory-to-sales ratio similar to what was observed in the data during the pandemic.[25] Nonetheless, I also explore a first moment shock-only supply disruption in Appendix D.

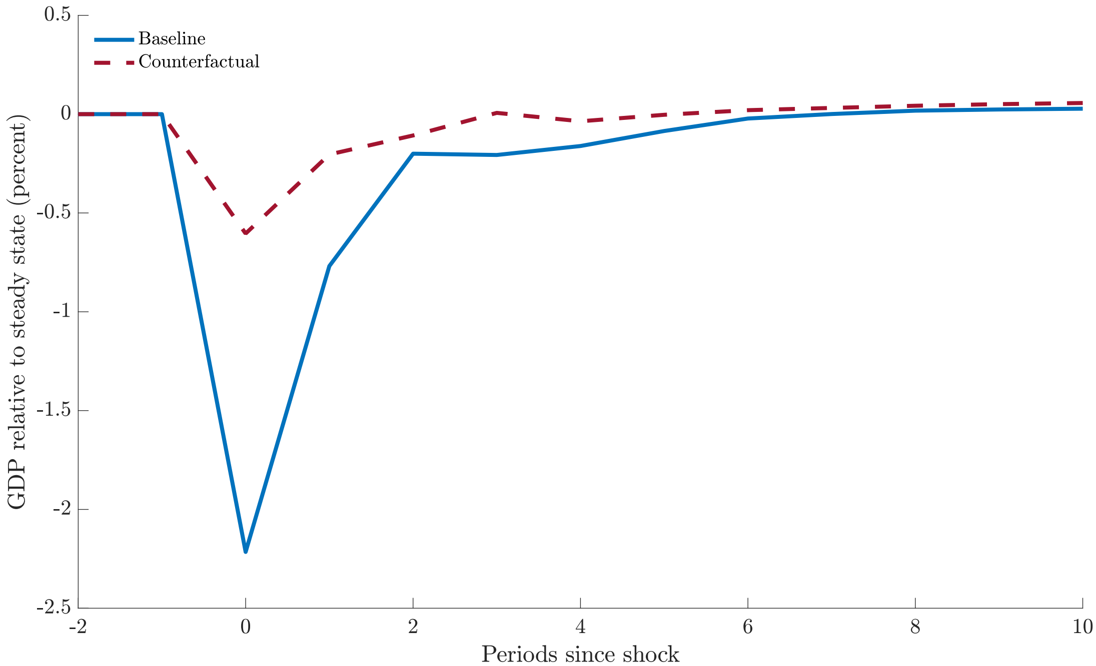
I calibrate the size of the order cost shock to reproduce a 2.2% GDP contraction in the baseline JIT model, in line with the annual contraction observed in U.S. GDP in 2020. I then introduce the same shock to the counterfactual model and compare the endogenous outcomes across the two economies. Figure 5 displays the output response to this unexpected shock. In addition, Figure 6 reports the key differences in endogenous responses between the two models amid the supply disruption.

Figure 5 shows that the JIT economy sees a roughly 1.7 percentage point excess output contraction on impact, with more than twice as much output lost along the transition back to steady state relative to the counterfactual.

Amid the supply disruption, expected order costs rise more in the baseline model, leading to a decline in order-placing probabilities relative to the counterfactual model as shown in Figure 6. As an optimal response to the decline in ordering probabilities, firms in both economies increase their order sizes. Order sizes, however, rise more in the baseline economy, mirroring the stronger

[25] Including a second moment shock to the order cost distribution is important for generating a rise in the inventory-to-sales ratio because it raises the uncertainty associated with to the optimal timing of orders. As a result, firms value inventories more and draw their stocks down more gradually. This implies that inventories decline more slowly than sales amid the shock, thereby raising the inventory-to-sales ratio.

Figure 5: Deeper Crisis with More Adoption



Note: The figure plots the output response to a fixed order cost shock that matches the 2.20% annual decline in real GDP in 2020. The persistence of the shock is set to 0.50.

decline in ordering probabilities.

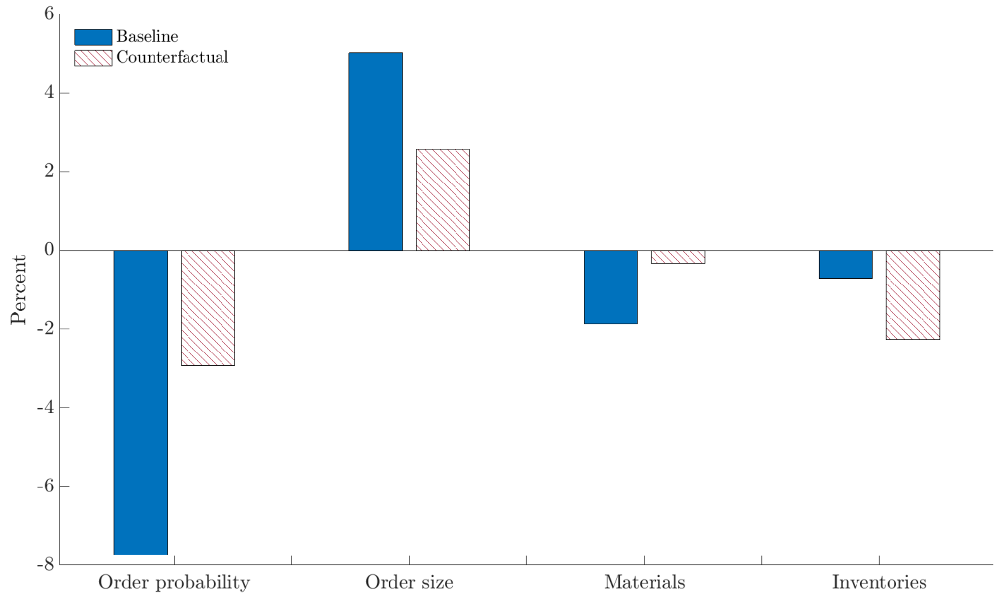
Despite the increase in order sizes, the extensive margin of ordering dominates so that aggregate orders decline in both economies though more so in the baseline. Material inputs also decline more strongly in the baseline economy as firms experience a sharper rise in uncertainty associated with fixed ordering costs, which increases the time between orders and slows material input usage.

Since inventory investment is the equal to the value of orders less materials, the stronger decline in aggregate orders relative to materials, and the general equilibrium decline in the price of orders in both economies, leads to a decline in inventory investment. This decline is more pronounced in the baseline economy. Hence, from the perspective of the following identity:

$$\text{Output} = \text{Final sales} + \text{Inventory investment},$$

we can characterize the excess output contraction in the baseline model as coming from both a

Figure 6: Sources of the Stronger Decline in the Baseline Model



Note: The figure plots endogenous responses to a fixed order cost shock that matches the 2.2% annual decline in real GDP in 2020. The persistence of the shock is set to 0.50. The bars reflect cumulative responses along the transition back to steady state.

relatively stronger decline in final sales and a stronger fall in inventory investment. The relative contributions of final sales and inventory investment to GDP growth in the baseline model are consistent with what was observed amid the onset of COVID-19.[26]

Amid the contraction, some JIT producers rethink their inventory management practices altogether. In the JIT model, we observe a 6% decline in the frequency of adoption as some firms abandon JIT and choose to hold more inventories. As a result, part of the stronger decline in ordering probabilities in the baseline model relative to the counterfactual model also reflects mode switching since firms that return to being non-JIT producers face higher fixed ordering costs.

A seemingly minor difference in inventory management strategies across the two models delivers a substantial difference in the extent to which the economy falls into crisis amid a supply

[26]In the data, final sales of domestic product declined by -1.7% in 2020. In the model, final sales decline by 1.6%.

disruption. The excess output loss amounts to slightly more than \$300 billion, a figure comparable to the funds appropriated to support businesses under the Paycheck Protection Program.[27] Lean inventory management therefore can play a meaningful role in determining the vulnerability of the economy to unanticipated supply disruptions. During these episodes, the extent to which inventories can serve as a stabilizing force is economically significant.

6.3 Understanding the Source of Supply Vulnerabilities

The heightened sensitivity to supply disruptions in the baseline model emanates from sharper declines in order-placing probabilities. In general, amid the supply disruption, ordering probabilities decline at low levels of inventories and rise at higher levels of inventories. Figure 7 provides further intuition by plotting relevant policies for a firm with a given productivity level as a function of inventories. Each panel plots two policies: one which reflects the steady state and the other which reflects the first period in which the supply disruption is realized. The left panel plots the ordering threshold policy function, $\xi^*(z, s, a)$ and the right panel plots the ordering probability.

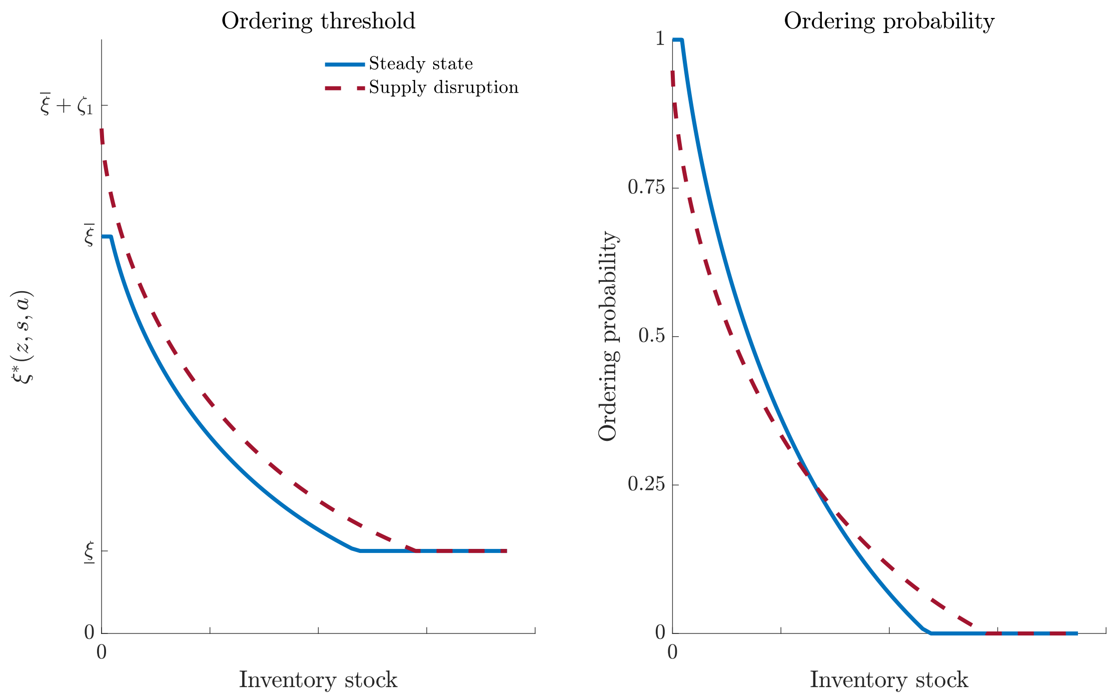
The downward sloping region of the threshold order policy reflects the relative value of placing an order, $\widetilde{\xi}(z, s, a)$, as defined in equation (8). Recall that the ordering threshold is $\xi^*(z, s, a) = \min(\max(\underline{\xi}, \widetilde{\xi}(z, s, a)), \overline{\xi})$. Given its idiosyncratic state, a producer places an order if the relative value of doing so exceeds the fixed order cost. At higher levels of inventories, the relative value of ordering additional materials declines until it eventually falls below the lower bound of the order cost distribution, where $\xi^*(z, s, a) = \underline{\xi}$. Here, the ordering threshold is flat and the probability of placing an order is zero.

In response to an increase in the upper bound of the fixed order cost distribution, the threshold order policy shifts up while ordering probabilities flatten out. These shifts in the policy functions reflect the first and second moment shocks to fixed order costs.[28]

[27] Coronavirus Aid, Relief, and Economic Security Act, H.R. 748, 116th Congress (2020).

[28] While the first moment shock reduces order probabilities across all inventory levels (i.e., ordering probabilities shift down), the second moment shock raises ordering probabilities at higher inventory levels (i.e., ordering probabilities flatten out).

Figure 7: Ordering During Supply Disruption



Note: The left panel plots a producer's ordering threshold as a function of its inventory stock in the steady state and amid a shock to fixed order costs at time $t = 1$. The right panel plots the probabilit of placing an order as a function of inventories in the steady state and amid the shock to fixed order costs at time $t = 1$.

At low levels of inventories, firms experience an increase in the relative value of placing an order, however, this is more than offset by the shock, making these firms *less* likely to place an order. For example, a firm that was willing to pay the maximum fixed order cost in the steady state, $\bar{\xi}$, to replenish its inventory stock is no longer willing to do so amid the shock since $\xi^*(z,s,a) < \bar{\xi} + \zeta_1$. Because the upper bound of the order cost distribution rises by more than the relative value of placing an order, firms at low levels of inventories experience a decline in order placing probabilities as depicted in the right panel of Figure 7.

On the other hand, firms operating at higher levels of inventories are less sensitive to the shock since they already have sizable inventory stocks and are therefore unwilling to pay large fixed order costs to procure additional materials even in the steady state. However, amid the shock, these firms acknowledge the likelihood they the may face a higher fixed order cost. As a result, the relative value of placing an order rises, making these firms *more* likely to place an order. Overall, while the relative value of placing an order rises across all inventory levels, firms with low inventories experience a decline in ordering probabilities while firms with high inventories experience a rise in ordering probabilities.

6.4 Accounting for the Countercyclical Relative Price of Inventories

While exploring a shock to fixed order costs exposes a stark vulnerability among lean producers, this exercise generates a decline in the relative price of inventories, q. Khan and Thomas (2007) cite a countercyclical relative price of inventories as an important feature of the data to match. At an annual frequency, the relative price of inventories increased by around 0.46 percent in 2020.[29] To replicate this feature of the data, I next repeat the exercise in the previous section and include a negative productivity shock to the orders producer. I assume that the orders producer's production technology is:

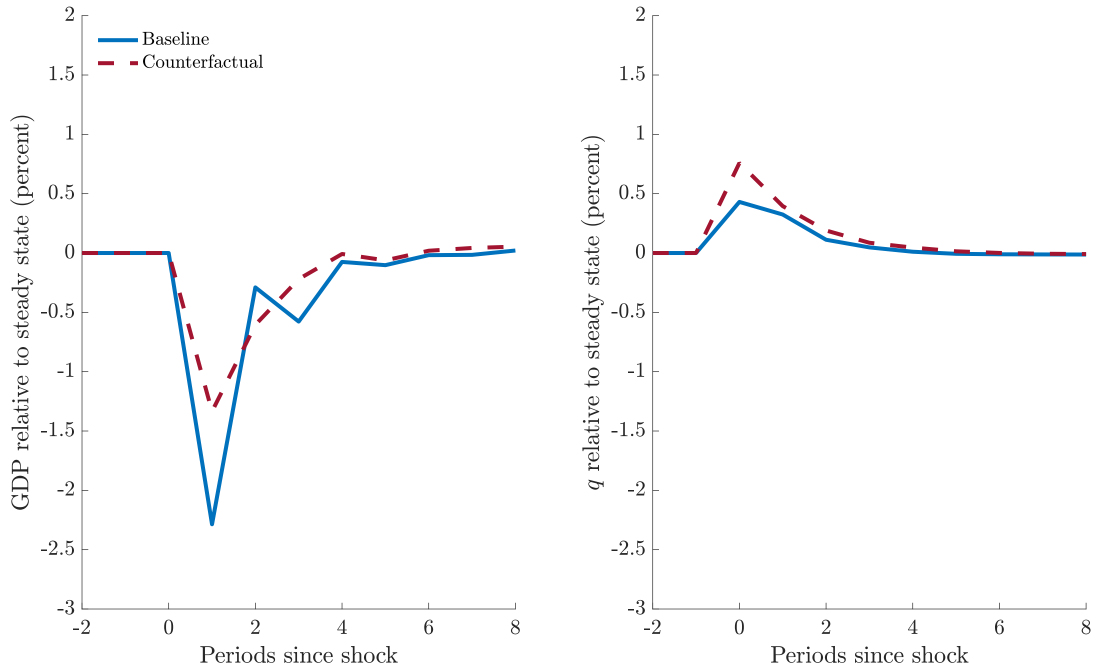
$$O = AK^{\alpha}L^{1-\alpha},$$

where $A = 1$ in the steady state. I then model two unanticipated shocks to the baseline economy: (1) the shock to the fixed order cost distributions, as before, and (2) a negative shock to A. I fix the persistence of both shocks to $\rho_{\zeta}^{\xi} = \rho_{\zeta}^{A} = 0.50$, and choose their sizes to replicate a -2.2 percent output contraction and a 0.46 percent increase in the relative price of inventories in the baseline economy, respectively.

The left panel of Figure 8 plots the output response in the baseline and counterfactual economies when subjected to the shocks to both the fixed and marginal cost of orders. The right panel of Figure 8 depicts the endogenous response of the relative price of inventories, q. Accounting for the increase in the relative price of orders, by introducing a negative productivity shock to the orders producer, somewhat mitigates the differences in output responses amid the contraction across the baseline and counterfactual models. However, the baseline economy nonetheless experiences a roughly 1 percentage point sharper output contraction on impact relative to the counterfactual

[29]This calculation is obtained by dividing the end-of-period annual private nonfarm inventory price deflator with the end-of-period annual implicit price deflator for final sales.

Figure 8: JIT Vulnerabilities to Broader Supply Disruption



Note: The figure plots the response of output (left panel) and the relative price of inventories (right panel) to shocks to the upper support of the fixed order cost distributions and to the productivity of the orders producer. The persistence of the shocks are set to 0.50 and their sizes are fixed to replicate a -2.20% decline in output and 0.46% increase in the relative price of orders in the baseline economy.

economy, indicating that the vulnerabilities associated with JIT, which stem from the shock to the fixed order cost distribution, remain important.

7 Conclusion

At the firm level, it pays to be lean. I provide empirical evidence of the benefits of JIT inventory management among publicly traded manufacturers. Upon adopting JIT, firms hold fewer inventories, and observe higher sales and smoother outcomes. JIT firms, however, are more susceptible to micro and macro supply disruptions. In a rich model of JIT production, the most productive firms adopt JIT which raises long-run firm profits by 8.8% and welfare by 0.38%. At the same time, JIT elevates firm vulnerability due to low inventory buffers. Amid an unexpected supply disruption, output in the estimated JIT economy contracts substantially more than a counterfactual economy with less JIT. Adoption, therefore, gives rise to an important tradeoff which implies that inventories can matter for aggregate fluctuations. Economists interested in understanding fluctuations within firms, and the responsiveness of the economy to aggregate shocks, particularly supply disruptions, should play close attention to inventories and inventory management practices.

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Appendix A Empirics

This section provides summary statistics of the data used in Section 2. The section also includes further details on the JIT adopters sample, the weather regression results, and an alternative measure of JIT among public firms.

A.1 Sample Construction

My data come from four sources. First, I make use of annual Compustat data to obtain information on firm-level inventory holdings, sales, and other outcomes. Second, I gather data on JIT adoption by reviewing firm financials and financial news. Third, I collect data from the Census M3 survey for the regressions estimating JIT sensitivity to aggregate supply conditions. Lastly, for the weather regressions, I collect county-level weather event data from NOAA and map them to firm headquarter zip codes.

Compustat Data

I make use of Compustat Fundamentals Annual data from 1971-2019. I keep only manufacturers (four-digit SIC codes between 2000-4000). In addition, I drop firm years in which acquisitions exceed 5% of total assets to avoid the influence of large mergers. To mitigate for any measurement error, I keep only those firms with non-missing and positive book value of assets, number of employees, inventories, and sales. All variables are winsorized at the top and bottom 0.5% of the empirical distribution.

Because the focus of the paper is on JIT, a concept that relates primarily to input inventories, I define the relevant measure of inventories to be the sum of raw material and works in process (`invrm+invwip`). This empirical definition also accords with the structural model developed in the main text in which producers carry stocks of inputs across time. My final sample consists of 2,580 unique firms. Table A1 reports summary statistics for the variables used.

Table A1: Compustat Summary Statistics

Variable name	Compustat code	Mean	Median	Standard Deviation	25%	75%
Log rder backlog	$\log(\texttt{ob}_t)$	2.656	2.610	2.211	1.147	4.078
Employment growth	$\frac{\Delta \texttt{emp}_t}{\texttt{emp}_t}$	0.002	0.004	0.233	-0.078	0.098
Inventory-to-sales	$\frac{\texttt{invrm}_t + \texttt{invwip}_t}{\texttt{sale}_t}$	0.145	0.109	0.156	0.066	0.173
Log sales	$\log(\texttt{sale}_t)$	4.358	4.281	2.181	2.836	5.831
Sales growth	$\frac{\Delta \texttt{sale}_t}{\texttt{sale}_{t-1}}$	0.070	0.067	0.293	-0.046	0.180
Log employment	$\log(\texttt{emp}_t)$	-0.323	-0.390	1.908	-1.732	0.999
Log property, plant, equipment	$\log(\texttt{ppent}_{t-1})$	2.563	2.452	2.392	0.855	4.151
Log finished goods inventories	$\log(\texttt{invfg})$	1.471	1.454	2.409	-0.196	3.175

Note: The table reports summary statistics for the relevant variables in the main text. The sample is constructed from Compustat Fundamentals Annual files for 1971-2019. Sample consists of 2,580 unique firms.

Adopters Dataset

First, I obtained data from JIT adopters, kindly provided to me by William Wempe (from his joint work with Michael Kinney), and Xiaodan Gao. These data include the years in which a Compustat manufacturer was identified to have adopted JIT (via Form 10-K filings, press releases, among other communications). See Kinney and Wempe (2002) and Gao (2018) for further details. After verifying these data, I conducted a separate search and uncovered an additional set of firms (reported in Table A2). After linking these identified firm-years to those in my Compustat dataset, I am left with a total of 185 idenified adopters in the manufacturing sector.

Table A2: Additional JIT Adopters

Firm	Compustat `gvkey`
Ford Motors	4839
General Motors	5073
Dell	14489
Motorola	7585
NCR	7648
Sunrise Medical	10185
Tellelabs	10420
Van Dorn Co	11101
Donnelly Corp	14462
Tuscarora	14578
Selectron	17110
Honeywell Inc	5693
ADC Telecommunications	1013
Sunbeam	1278
Boeing	2285
Campbell	2663
Cascade Corporation	2802
Caterpillar	2817

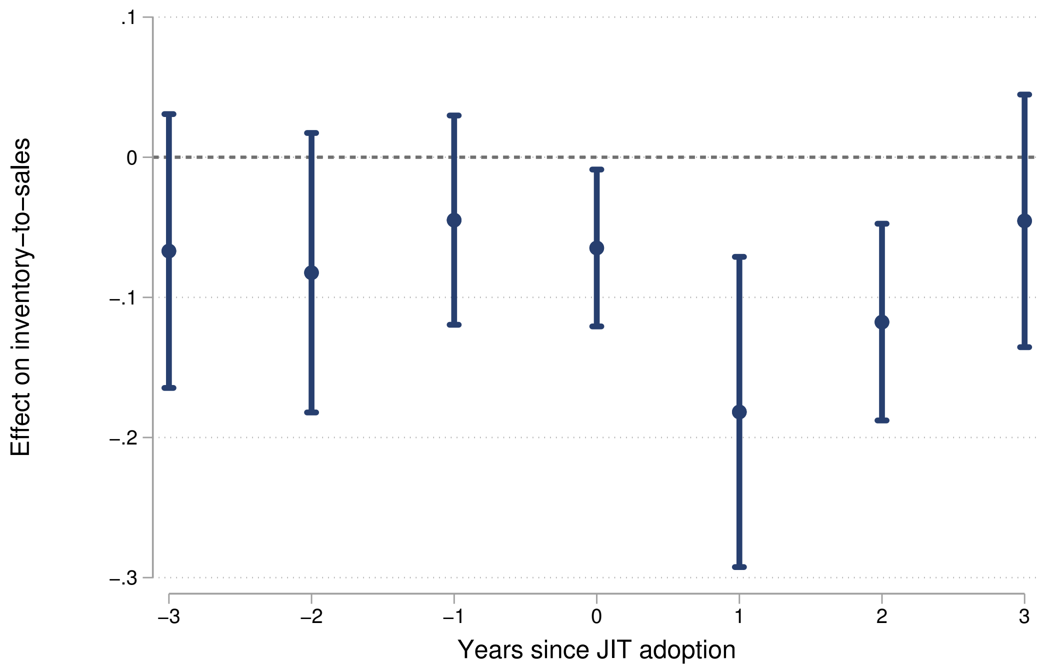
Note: The table reports the additional JIT adopters that were added to the original set of adopters.

While I estimate the model in a manner that accounts in part for cross-sectional JIT measurement error, time series measurement error could also be a concern. If, for instance, a firm adopts JIT in a given year, but does not announce that it is a JIT firm until a subsequent year, then the primary measure of JIT utilized in the main text would be subject to an additional form of measurement error. While such measurement error would imply that my reported estimates are attenuated, Figure A1 provides evidence that the recorded years of adoption are accurate. I run the following regression:

$$y_{ijt} = \gamma \text{adopt}_{ijt} + \mathbf{X}'_{ijt}\beta + \delta_{jt} + \delta_i + \varepsilon_{ijt}$$

where the outcome of interest is the inventory-to-sales ratio, and adopt_{ijt} is an indicator taking on a value of one only in the recorded year of adoption. Industry-by-year and firm fixed effects are specified along with a set of controls which include firm size, age in sample, finished goods inventories, and net income. The figure plots 95% confidence intervals for a three-year window around the recorded date of adoption, and shows that inventory holdings decline in the year of adoption and for the subsequent two years.

Figure A1: Validation of JIT Indicator



Note: The figure plots the estimated effect of JIT adoption on the level of inventory-to-sales. 95% confidence bands are displayed alongside point estimates.

A.2 Alternative Measure of JIT Adoption

To explore the robustness of the text-based measure of JIT adoption, I develop an alternative measure by taking a time series approach. Rather than using the inventory-to-sales ratio to validate a measure of JIT, as I do above, here instead I use observed declines in inventory-to-sales ratios to detect JIT.

I define inventory-to-sales thresholds by computing the median inventory-to-sales ratio within narrowly-defined SIC industries between 1970 and 1974. From 1975 onward, I define a firm to be JIT if its inventory-to-sales ratio falls below its industry-defined historic threshold. In other words, if a firm's inventory-to-sales ratio falls below its industry's median 1970-1974 inventory holdings, then that firm must have adopted JIT in some form.

An appealing aspect of this approach is that measures JIT adoption among a wider variety of firms (e.g., manufacturers and retailers), whereas the text-based measure if focuses solely on

Table A3: JIT Adoption and Firm Performance

	Inventory-to-Sales	Sales	Sales per worker
JIT	-0.611***	0.133***	0.147***
	(0.021)	(0.012)	(0.011)
Fixed effects	Firm, Sector × Year	Firm, Sector × Year	Firm, Sector × Year
Firms	2,517	2,517	2,517
Observations	22,051	22,051	22,051

Note: The table reports panel regression results based on regression (1). The dependent variables are log inventory-to-sales, log sales, and log sales per worker. Lags of log employment, log capital stock, and log order backlogs are specified as controls. Two-digit SIC codes are specified in the sector-by-year fixed effects. Standard errors are double clustered along the firm and fiscal year levels. The standard deviations of the dependent variables are 0.86, 2.19, and 0.89, respectively. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

manufacturers. Of the JIT adopters found through the text-based measure, this alternative measure picks up about 80% of them. In the subsequent section, I show that the empirical facts discussed in the main text also arise when using this sample, demonstrating that these stylized facts are robust to alternative measures of JIT.

Empirical Facts

Using these data, I revisit the four facts about JIT adopters presented in the main text. First, JIT adoption is associated with improvements in firm performance measures. Based on Table A3 , adopters experience a 61% decrease in inventory holdings, a 13% increase sales, and a 15% increase in sales per worker. Moreover, Table A4 indicates that JIT adopters experience less micro volatility. Based on these estimates, adopters see an 8% to 14% decrease in measured volatility.

In addition, JIT adopters are more sensitive to fluctuations in aggregate unfilled orders as shown in Table A5. The table indicates that a 1% increase in unfilled orders relative to new orders is associated with a roughly 0.15% decrease in sales among non-adopters. Adopters experience an additional sales decline of 0.09%, comparable to the baseline coefficients reported in Table 3.

Finally, Table A6 reports analogous weather event results and shows again that sales decline by about 6.5% more for JIT adopters relative to non-JIT adopters. With the new measure of adopters,

Table A4: JIT Adoption and Firm Volatility

	Sales growth	Employment growth
JIT	-0.140***	-0.079***
	(0.029)	(0.027)
Fixed effects	Sector $\times$ Year	Sector $\times$ Year
Firms	2,557	2,552
Observations	16,482	16,409

Note: The table reports panel regression results based on regression (2). The dependent variables are rolling five-year standard deviations of firm sales and employment growth. Lagged log capital stock is specified as a control variable. Two-digit SIC codes are specified in the sector-by-year fixed effects. Standard errors are double clustered along the firm and fiscal year levels. The standard deviation of both dependent variables is 0.77. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

the employment regression no longer yields statistically significant coefficients.

Table A5: JIT Adoption and Aggregate Unfilled Orders

	(1)	(2)
Log unfilled orders-to-new orders	-0.149*	
	(0.078)	
Log unfilled orders-to-new orders × JIT	-0.088***	-0.055***
	(0.020)	(0.016)
Fixed effects	Firm	Firm, Sector × Year
Firms	2,563	2,517
Observations	22,459	22,051

Note: The table reports panel regression results from regression (3). The dependent variable is the log of firm sales. Lagged firm capital stock, firm employment, firm order backlog, aggregate new orders, and contemporaneous JIT adoption indicator are specified as controls. Two-digit SIC codes are specified in the sector-by-year fixed effects. Standard errors are double clustered along the firm and fiscal year levels. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Table A6: JIT Adoption and Weather Events

	Sales		Employment	
	(1)	(2)	(3)	(4)
Weather event	0.022		0.030	
	(0.023)		(0.023)	
Weather event × JIT	-0.015	-0.065*	-0.029	-0.067
	(0.023)	(0.038)	(0.023)	(0.051)
Fixed effects	Firm, Supplier, Year	Firm, Supplier×Year	Firm, Supplier, Year	Firm, Supplier×Year
Firms	359	177	359	177
Observations	4,216	1,215	4,216	1215

Note: The table reports panel regression results from Compustat Annual Fundamentals based on regression (4). The dependent variables are log sales and log employment. Finished goods inventory is specified as a control variable. Standard errors are double clustered at the customer-supplier level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Appendix B Model

B.1 Intermediate Goods Firm

The intermediate goods firm problem is:

$$\max_{K,L} p\Big[qK^{\alpha}L^{1-\alpha} - RK - wL\Big]$$

The assumption that the intermediate goods firm utilizes a Cobb-Douglas production technology to produce implies that the intermediate goods firm's value can be expressed as a linear function of the aggregate capital stock. As a result, one can solve for q analytically. The price of the intermediate good is:

$$q = \left(\frac{1+r}{\alpha}\right)^{\alpha}\left(\frac{w}{1-\alpha}\right)^{1-\alpha}$$

B.2 Equilibrium

An equilibrium is a set of functions,

$$\big\{V^A, V^O, V^*, V^P, s^*, s', \xi^*, a', K, L, p, w, q, \Gamma_\mu\big\},$$

such that:

1. The household's first order conditions hold:

$$p = \frac{1}{C}, \quad w = \phi C.$$

2. The intermediate goods firm first order conditions hold:

$$w = (1-\alpha)q\left(\frac{K}{L}\right)^{\alpha} \quad R = \alpha q\left(\frac{L}{K}\right)^{1-\alpha}.$$

3. V^A, V^O, V^*, V^P solve the final goods firms' problem.

4. Market for final goods clears:

$$C = \int\int y(z,s^*,s',a,\xi)dF(\xi^*)d\mu(z,s,a) + \int\int y(z,s,s',a,\xi)[1-dF(\xi^*)]d\mu(z,s,a)$$
$$-\frac{c_m}{2}\left(\int\int s'(z,s*,a)^2 dF(\xi^*)d\mu(z,s,a) + \int\int s'(z,s,a)^2[1-dF(\xi^*)]d\mu(z,s,a)\right) - K.$$

5. Market for orders clears:

$$\left(\frac{(1-\alpha)q}{w}\right)^{\frac{1-\alpha}{\alpha}} K = \int\int [s^*(z,s,a)-s]dF(\xi^*)d\mu(z,s,a),$$

where the left hand side denotes the supply of orders, $K^\alpha L^{1-\alpha}$.

6. Market for labor clears:

$$H = \int\int n(z,s^*,s',\xi)dF(\xi^*)d\mu(z,s,a) + \int\int n(z,s,s',a,\xi)[1-dF(\xi^*)]d\mu(z,s,a)$$

$$+\int\left[\int_0^{\xi^*(z,s,a)} \xi dF(\xi)\right]d\mu(z,s,a) + \int a'(z,s,a)[(1-a)c_s + ac_f]d\mu(z,s,a) + \left(\frac{(1-\alpha)q}{w}\right)^{\frac{1}{\alpha}} K.$$

On the right hand side, the first two terms refer to labor demand from the final goods firms, the third term refers to the labor-denominated order cost, the fourth term refers to the labor-denominated adoption costs, and the final term refers to labor demand from the orders producer, L.

7. The evolution of the distribution of firms is consistent with individual decisions:

$$\Gamma_\mu(z,s,a) = \int\int\int 1_{\mathbb{A}} d\mu(z,s,a)dF(\xi)d\Phi(\varepsilon_z)$$

$$\mathbb{A}(z',s',a',\xi,\varepsilon_z;\mu) = \{(z,s,a)|s'(z,s,a,\xi;\mu) = s', z' = \rho_z + \sigma_z\varepsilon_z, a'(z,s,a,\xi;\mu) = a'\}$$

$$\Phi(x) = \mathbb{P}(\varepsilon_z \leqslant x),$$

B.3 Numerical Solution

The model is solved using methods that are standard in the heterogeneous firms literature. The exogenous productivity process is discretized following Tauchen (1986) which allows me to express the AR(1) process for log firm productivity as a Markov process. I select $N_z = 11$ grid points for idiosyncratic productivity and $N_s = 200$ grid points for the endogenous inventory holding state. Considering the binary adoption state, this implies that the discretized model has 4,400 grid points.

I solve for the policy functions via value function iteration which is accelerated by the use of the MacQueen-Porteus error bounds (MacQueen, 1966; Porteus, 1971). This acceleration method makes use of the contraction mapping theorem to obtain bounds for the true (infinite horizon) value function. These bounds are used in order to produce a better update of the value function. The ergodic distribution of firms is obtained via nonstochastic simulation as in Young (2010). This histogram-based method overcomes sampling error issues associated with simulating individual firms in order to obtain the stationary cross-sectional distribution.

Operationally, I solve the model by initiating a guess of the final goods price, p_0. Using the household and order producer's optimality conditions, I then obtain q_0 and w_0 given the guess p_0. From here, I solve the firm's problem via value function iteration and then obtain the ergodic distribution. Using the policies and ergodic distribution, I compute aggregates and the associated market clearing error from the household's optimality condition. I update the price based on this error via bisection.

For the unexpected shock exercises, I implement a standard shooting algorithm used to model deterministic dynamics. I fix the duration of the transition to a predetermined length T so that the model reaches steady state at $T+1$. I then solve the final goods firms problem backwards, obtaining a set of time-indexed policy functions. Using these policies, I push the distribution of final goods firms forward. With the time-indexed policies and weights in hand, I compute aggregates at each point in time and iterate on prices until the final goods market clears in each period, $\frac{1}{p_t} = C(p_t)$.

Appendix C Estimation

In this section, I detail the estimation of the model and provide additional results relating to identification. The final subsection reports the counterfactual parameter estimates and model fit.

C.1 Simulated Method of Moments

The parameter vector to be estimated is $\theta = \big(\rho_z \;\; \sigma_z \;\; \underline{\xi}_{NA} \;\; \overline{\xi}_{NA} \;\; \underline{\xi}_A \;\; \overline{\xi}_A \;\; c_s \;\; c_f \;\; c_m\big)'$. Estimating θ requires making a guess, θ_0, solving and simulating the model, and computing the different moments. I collect the targeted empirical moments in a stacked vector $m(X)$ which comes from my Compustat sample. I next stack the model-based moments, which depend on θ, in the vector $m(\theta)$. Finally I search the parameter space to find the $\widehat{\theta}$ that minimizes the following objective

$$\min_{\theta} \big(m(\theta) - m(X)\big)' W \big(m(\theta) - m(X)\big)$$

where W is the optimal weighting matrix, defined to be the inverse of the covariance matrix of the moments. I obtain the covariance matrix via a clustered bootstrap, allowing for correlation within firms. I estimate the parameter vector via particle swarm, a standard stochastic global optimization solver.

The limiting distribution of the estimated parameter vector $\widehat{\theta}$ is

$$\sqrt{N}(\widehat{\theta} - \theta) \xrightarrow{d} N(0, \Sigma)$$

where

$$\Sigma = \left(1 + \frac{1}{S}\right)\left[\left(\frac{\partial m(\theta)}{\partial \theta}\right)' W \left(\frac{\partial m(\theta)}{\partial \theta}\right)\right]^{-1}$$

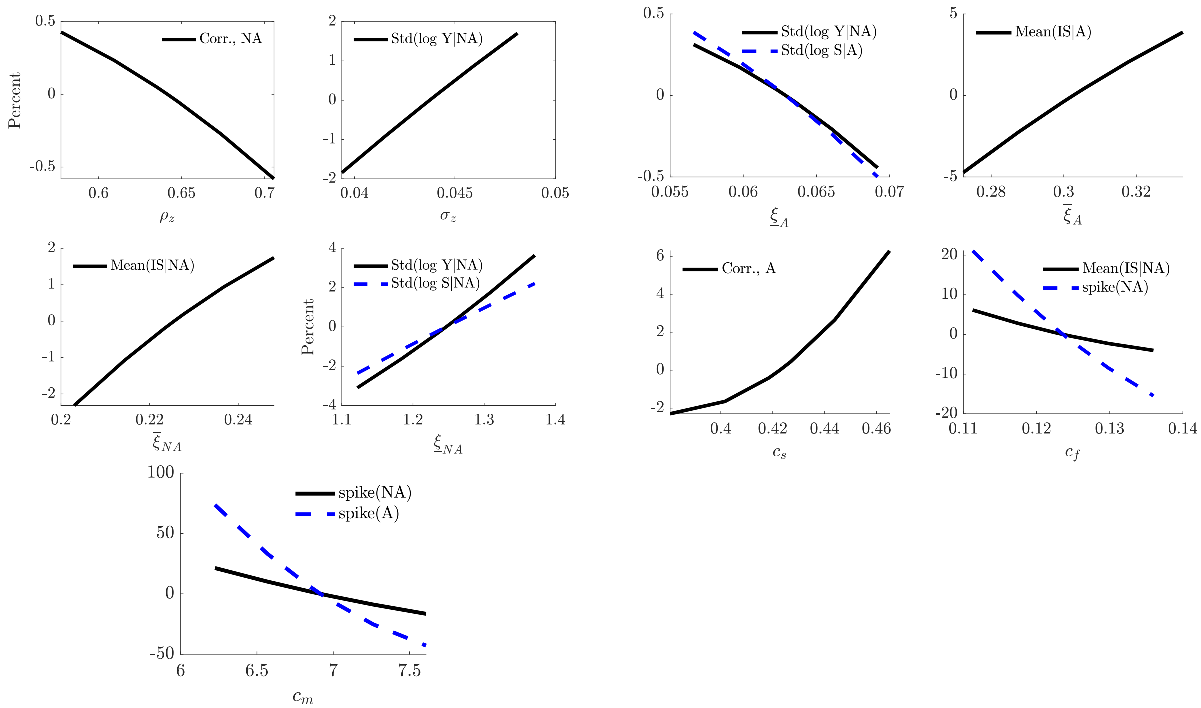
and S is the ratio of the number of observations in the simulated data to the number of observations in the sample.[30] I obtain the standard errors by computing the secant approximation to the partial derivative of the simulated moment vector with respect to the parameter vector. Given the

[30] S is set to be approximately 8.

discontinuities induced by the discretized state space, I select a step size of 1%.

C.2 Identification

Figure C1: Monotonic Relationships



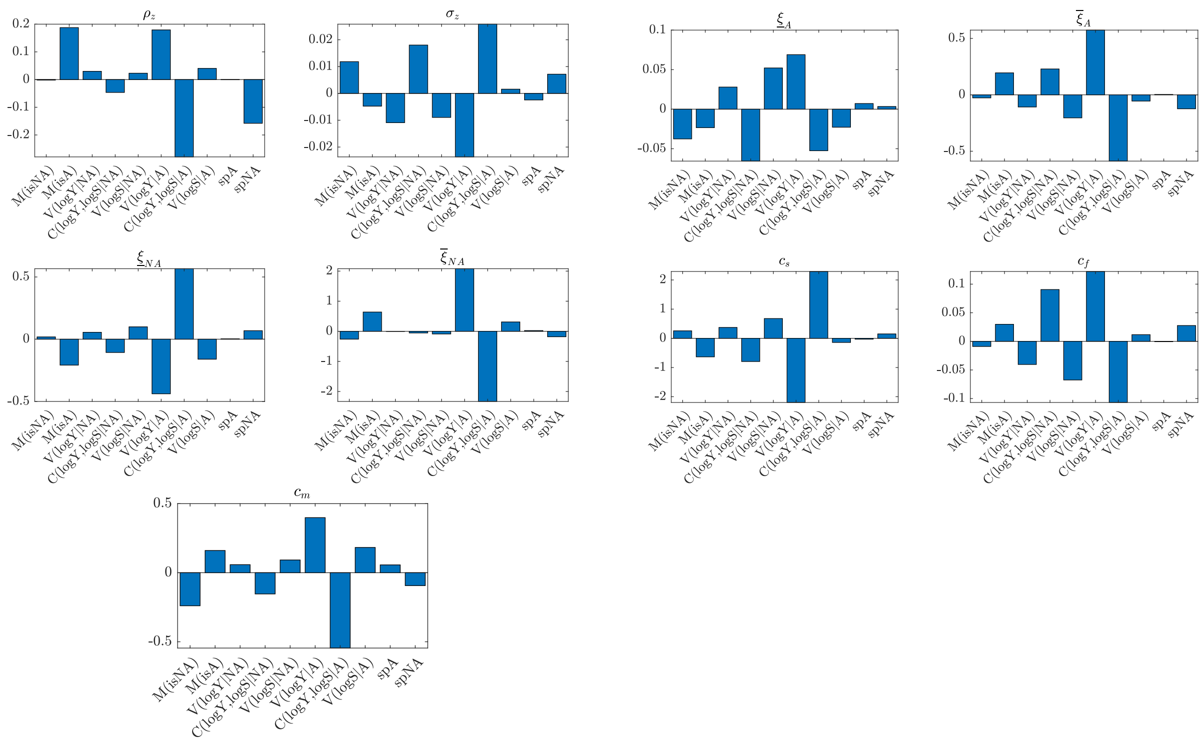
Note: The figure plots the changes in select moments to changes in the parameters, in percent relative to moment at estimated parameter values.

The 10 moments jointly determine the 9 parameters that reside in vector θ. To supplement the discussion on monotone relationships from the main text, Figure C1 reports the monotone relationships between selected moments and parameters. Figure C2 reports the sensitivity of each of the nine parameters to changes in each of the moments. These results come from an implementation of Andrews et al. (2017). The sensitivity of $\widehat{\theta}$ to $m(\theta)$ is

$$\Lambda = -\left[\left(\frac{\partial m(\theta)}{\partial \theta}\right)' W \left(\frac{\partial m(\theta)}{\partial \theta}\right)\right]^{-1} \left(\frac{\partial m(\theta)}{\partial \theta}\right)' W$$

I then transform this matrix so as that the interpretation of the coefficients is the effect on each parameter of a one standard deviation change in the respective moments.

Figure C2: Sensitivity



Note: The figure plots sensitivity estimates as in Andrews et al. (2017). These estimates describe the changes in each of the nine parameters to a one standard deviation increase in each moment.

C.3 Counterfactual Model Estimates and Fit

Table C1: Estimated Counterfactual Parameters

Description	Parameter	Estimate	Standard error
Productivity shock persistence	ρ_z	0.642	-
Productivity shock dispersion	σ_z	0.044	-
Order cost lower bound (non-JIT)	$\underline{\xi}_{NA}$	0.279	0.0003
Order cost upper bound (non-JIT)	$\overline{\xi}_{NA}$	0.972	0.0014
Order cost lower bound (JIT)	$\underline{\xi}_{A}$	0.085	0.0005
Order cost upper bound (JIT)	$\overline{\xi}_{A}$	0.493	0.0003
Sunk cost of adoption	c_s	0.521	0.0012
Continuation cost of adoption	c_f	0.132	0.0007
Carrying cost	c_m	6.916	-

Note: The table reports the point estimates and standard errors for the nine estimated parameters. Standard errors obtained via numerical differentiation.

Table C2: Counterfactual Model vs. Empirical Moments

Moment	Model	Data
Mean(inventory-sales ratio|non-adopter)	0.166	0.155
		(0.002)
Mean(inventory-sales ratio|adopter)	0.126	0.111
		(0.007)
Std(log sales |non-adopter)	0.604	0.359
		(0.004)
Corr(log sales, log inventories|non-adopter)	0.894	0.732
		(0.003)
Std(log inventories|non-adopter)	0.469	0.411
		(0.004)
Std(log sales |adopter)	0.475	0.411
		(0.031)
Corr(log sales, log inventories|adopter)	0.777	0.843
		(0.034)
Std(log inventories|adopter)	0.457	0.495
		(0.044)
Spike(inventory-sales ratio|non-adopter)	0.200	0.227
		(0.007)
Spike(inventory-sales ratio|adopter)	0.027	0.078
		(0.028)

Note: The table reports model-based and empirical moments along with standard errors of the empirical moments.

Appendix D Robustness

In this section I provide robustness checks relating to the vulnerability of a JIT economy to supply disruptions and other disturbances. I further examine the sensitivity of JIT to supply disruptions by considering different parameterizations. I then analyze the role that anticipation plays in the sensitivity of JIT to supply disruptions. Finally, I examine the vulnerability of a JIT economy to only a first moment shock to fixed order costs.

D.1 Sensitivity Analysis

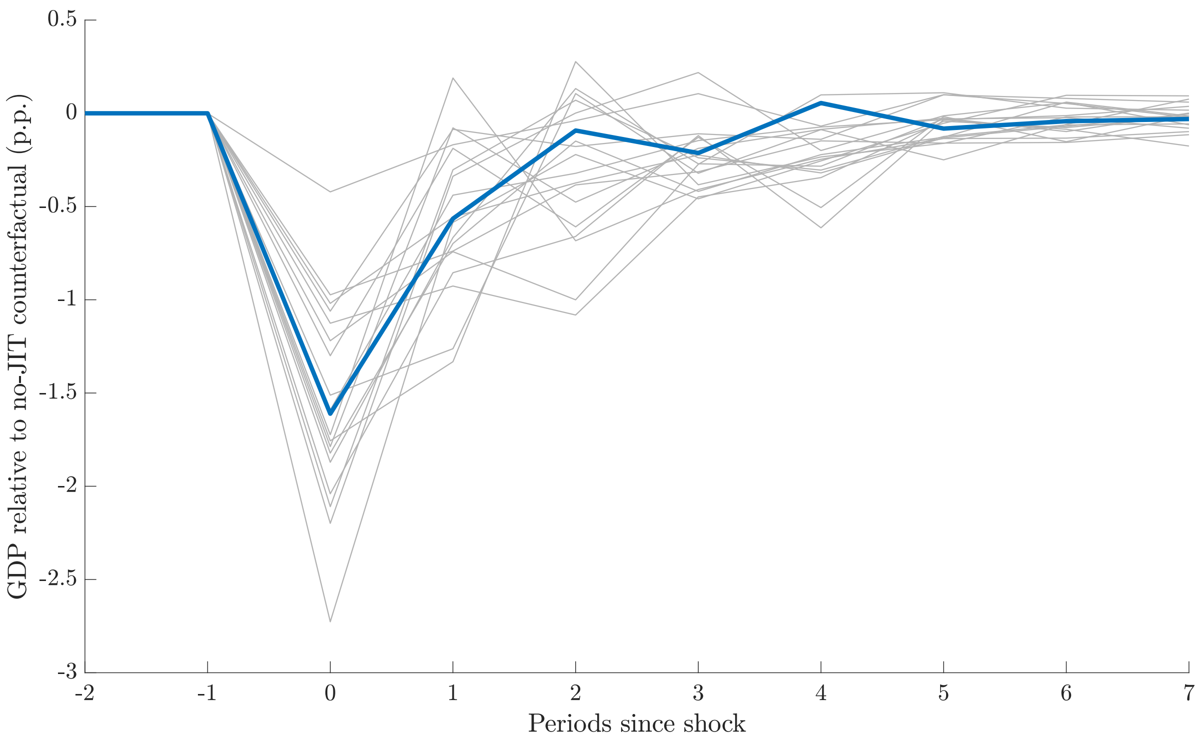
Table D1: Alternative Parameterizations

Description	Parameter	Value	Value
Idiosyncratic productivity persistence	ρ_z	0.60	0.70
Idiosyncratic productivity volatility	σ_z	0.035	0.055
Order cost lower bound (non-adopters)	$\underline{\xi}_{NA}$	0.11	0.27
Order cost upper bound (non-adopters)	$\overline{\xi}_{NA}$	1.00	1.50
Order cost lower bound (adopters)	$\underline{\xi}_{A}$	0.04	0.09
Order cost upper bound (adopters)	$\overline{\xi}_{A}$	0.25	0.38
Sunk cost of adoption	c_s	0.35	0.48
Continuation cost of adoption (adopters)	c_f	0.09	0.20
Carrying cost	c_m	5.00	7.50

Note: The table reports the alternate parameterizations chosen to compute the excess sensitivity to supply disruptions associated with JIT.

Table D1 reports a number of different parameter specifications. I vary all parameters in different directions. Figure D1 plots the excess contraction amid a supply disruption between the JIT and counterfactual economies. Across all specifications, output contracts more sharply in the JIT economy than in the counterfactual.

Figure D1: JIT Vulnerabilities with Alternative Parameters



Note: The figure plots the relative GDP contraction in the baseline economy versus the counterfactual (i.e. GDP relative to steady state in baseline minus GDP relative to steady state in counterfactual). The thick blue line denotes the baseline parameterization estimated in the main text, and the thin grey lines represent the alternative parameterizations. The different parameterizations are detailed in Table D1.

D.2 Partial Anticipation

In this subsection, I allow for there to be uncertainty as to whether the supply disruption occurs in period t. This uncertainty is fully resolved in period t regardless of whether or not the shock comes to pass.

Let λ denote the probability that the fixed order cost shock is realized at time t. Recall that final goods firms face the following problem in the production stage:

$$V^P(z, \widetilde{s}, a) = \max_{s' \in [0, \widetilde{s}]} \pi(z, \widetilde{s}, s', a) + \beta \mathbb{E}\big[V^A(z', s', a')\big].$$

In period $t-1$, however, the expectation is not only taken across idiosyncratic productivity realizations but across the realization of the supply disruption as well:

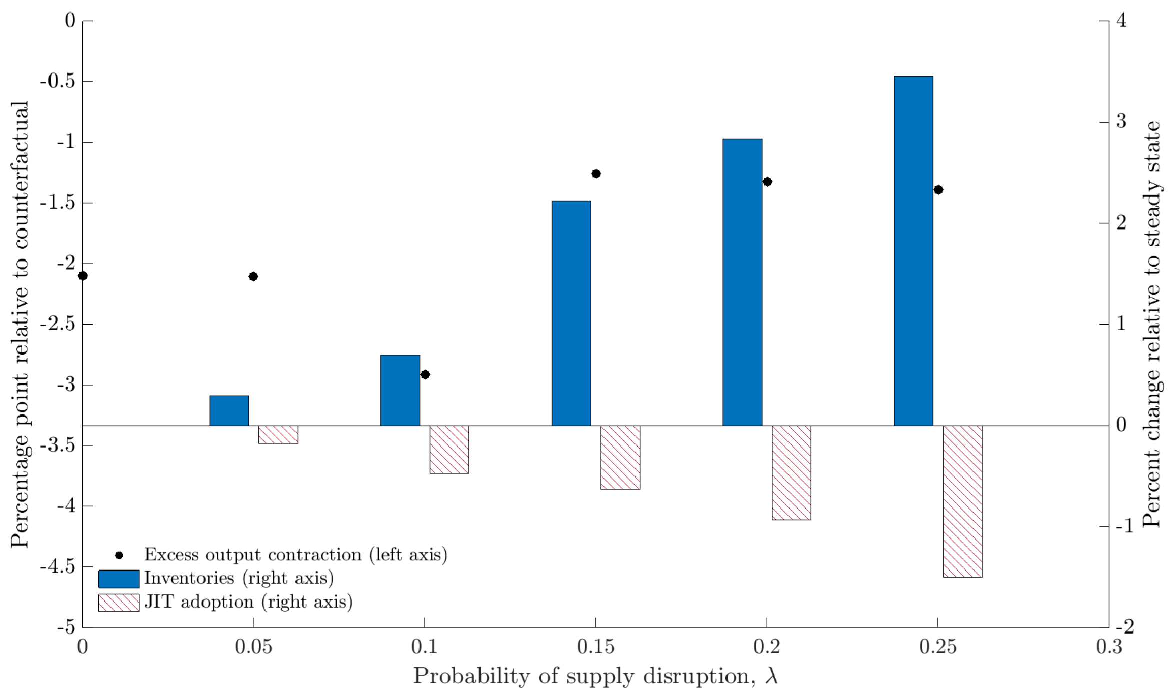
$$V^A(z', s', a') = \lambda V^A_{\text{Disruption}}(z', s', a') + (1-\lambda) V^A(z', s', a').$$

I evaluate the dynamics amid the fixed order cost shock by implementing an algorithm similar to the unanticipated case. I begin with an initial guess for prices and work backwards to obtain a sequence of time-indexed value and policy functions. With these in hand, I proceed to a forward step in which I obtain a time-indexed distribution of firms across z, s, and a. From here, I compute aggregates, check for market clearing, and update the prices until convergence to a specified tolerance.

Figure D2 plots two relevant quantities. On the right axis, I plot the changes in inventory stock and in JIT frequency in the period leading up to the shock. As the likelihood of the realization of a widespread supply disruption rises, we observe an increase in economy-wide inventory stocks accumulated by firms in anticipation of the shock. Intuitively, with the prospect of a widespread disaster on the horizon, firms will optimally hold added precautionary stocks of inventories. The aggregate inventory stock rises by about 1% when the likelihood of a supply disruption is 10%. The risk of a supply disruption also makes it optimal for firms to switch out of JIT adoption, which is costly to maintain in an environment in which inventories are more highly valued. The frequency of JIT adoption falls by about -0.5% when the likelihood of a supply disruption is 10%. Overall, although anticipation somewhat changes the pre-shock steady state, these changes are quantitatively small.

On the left axis, I plot the total excess output contraction experienced in the estimated economy relative to the counterfactual (in percentage points). When there is no anticipation ($\lambda = 0$) we recover a roughly 2.1percentage point excess output contraction along the transition. Despite the added precautionary inventory holdings among firms, there is still a sizable excess drop in output in the JIT economy for a range of probabilities, indicating that the sensitivity of JIT to supply disruptions discussed in the main text is robust to the anticipation modeled here. There are two reasons for this result. First, the convex storage cost reduces the value of carrying precautionary stocks of inventories across time given the relatively low probabilities assigned to the shock. Second, the cost of not building precautionary stocks of inventories is mitigated by the fact that the distribution of individual firm outcomes is truncated on the left. The worst case scenario for firms in the model is stocking out and earning zero profits. As a result, even with partial anticipation, firms are not particularly sensitive the prospect of the large supply disruption that might come to pass.

Figure D2: JIT Tradeoff Robust to Anticipation



Note: The dots, which correspond to the left axis, display the excess output contraction (relative to the counterfactual) for different disaster probabilities. On the right axis, the bars plot the percent increase in inventory stocks (solid blue) and percent decrease JIT adoption (striped red).

D.3 Assuming Only a First Moment Shock to Order Cost Distributions

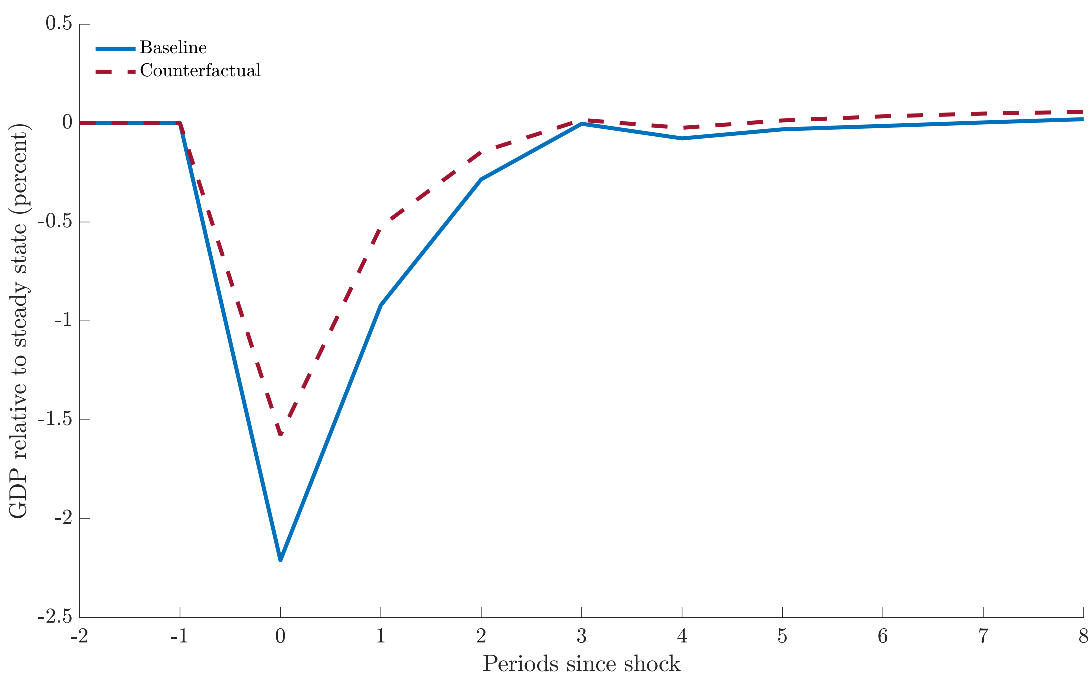
In this section I consider a shock to average order costs. This exercise differs form the one in the main text because I now assume that the upper and lower bounds of the order cost distributions are shifted,

$$\underline{\xi}_t = \underline{\xi} + \zeta_t \qquad \text{and} \qquad \overline{\xi}_t = \overline{\xi} + \zeta_t,$$

where $\zeta_t = \rho_\zeta^\xi \zeta_{t-1}$ and $\rho_\zeta^\xi = 0.50$.

Figure D3 plots the output response to the shock in the baseline and counterfactual models, with the shock calibrated to generate a 2.2% contraction in the baseline model. The results confirm that the baseline economy exhibits heightened sensitivity to a first moment shock to order cost distributions. Paired with the results in the main text, we can conclude that the baseline JIT economy is even more sensitive to shocks to the upper bound of the order cost distribution.

Figure D3: Shock to Average Fixed Order Costs Only



Note: The figure plots the output response to an order cost shock that matches a 2.2% annual decline in real GDP in 2020. The persistence of the shock is set to 0.50.