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 measures the share of public manufacturers that have adopted JIT and quantifies a trade-off 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 chain pressures. I explain these facts in a structurally estimated general equilibrium model of JIT production. Relative to a counterfactual economy without JIT, the baseline model implies higher firm profitability in normal times but a deeper contraction amid a supply disruption. Moreover, a transition to an equilibrium with less JIT and larger inventory buffers leads to a roughly 4% output loss.

Keywords: Inventory investment. Heterogeneous firms. Supply disruption. 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 from suppliers.[1] Firms adopt JIT 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, JIT, often also called lean inventory management, has contributed to the approximately 25% 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 different 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 trade-off from a 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 build a measure of the share of public manufacturers that adopt JIT by comparing firm inventory holdings to historical industry-level inventory holdings. My measure of JIT reflects any force that leads to a decline in inventories. Many of these forces likely facilitated JIT adoption. For example, improvements in transportation and logistics made it feasible for more firms to arrange for small and frequent delivery of materials. In addition, improvements in information technology allowed firms to better communicate with suppliers and more accurately forecast demand. Finally,

[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.

over time, a new cohort of managers trained in JIT best practices increased the likelihood of a successful transition to JIT. According to my measure, JIT adoption increased in popularity from 1980 through the late 2000s. In Appendix A.2, I validate my approach by comparing JIT firms identified from my measure to a narrower set of JIT firms identified in the accounting literature through recorded public announcements.

Using my measure of JIT adoption, I 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 roughly 30% increase in sales and sales per worker, and a 55% increase in earnings. In addition, JIT is associated with between a 5% to 19% decline in sales growth volatility, employment growth volatility, and earnings growth volatility.

I then exploit variation external to the firm and document that JIT adopters appear to be more exposed to supply disruptions as proxied by fluctuations in the New York Fed Global Supply Chain Pressure Index (GSCPI). At the firm level, JIT firms experience an additional 2% decline in sales compared to non-JIT firms amid an increase in supply chain pressures. 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 1980 to 2019. Relative to a counterfactual economy without JIT, the baseline economy features lower overall inventory holdings and higher output. Moreover, although JIT makes firms more sensitive to idiosyncratic productivity realizations in the model, firm-level volatility nonetheless declines relative to the counterfactual model because JIT adoption leads to a reduction in the variance of fixed ordering costs.

Whereas an economy populated by JIT producers experiences higher output in equilibrium than an economy without JIT, the former is also 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 along the transition that is 65% larger than in the counterfactual economy. An unexpected spike in fixed order costs causes firms' ordering inaction regions to expand, leading to a decline in orders. With fewer material inputs on hand, output and sales decline, more so in the baseline economy where firms carry fewer stocks begin with.[4] In Appendix D.4 I show that this result also generally holds in a version of the model in which there is aggregate uncertainty about fixed order costs.

Finally, in light of recent debates about re-shoring and achieving supply chain "resilience," I examine how the JIT economy would transition to a new steady state that features less JIT adoption and larger inventory buffers. I find that output falls by about 4% along the transition to an equilibrium that features recently observed higher levels of inventory holdings. Furthermore, I find that consumption-equivalent welfare declines by -0.72%, reflecting both the costs of holding excess inventories and the foregone benefits of smoother micro-level outcomes.

In short, my empirical and theoretical analysis quantifies a trade-off 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 a supply disruption, an economy populated by more JIT firms experiences a deeper contraction.

Inventory investment has long been of interest as a potential source of macroeconomic volatility

[4]If firms were able to jointly choose their selling price and end-of-period inventories, then it would be in principle possible for firms to adjust their price in response to a shock to their optimal inventory holdings. Firms that run low on inventories would like to raise their prices in order to meet demand, but may stockout in the presence of pricing frictions, as mentioned in Cavallo and Kryvtsov (2023). JIT firms would be more likely to stock out. Moreover, in an environment in which prices are fully flexible, Alessandria et al. (2023) find that an economy with initially lower aggregate inventories experiences more adverse outcomes in response to a lengthening of delivery lags. As a result, introducing a pricing decision that occurs jointly with the inventory decision is unlikely to overturn the result that a JIT economy is more exposed than a no JIT economy to an unexpected supply disruption.

(Ahmed et al., 2004; McConnell and Perez-Quiros, 2000; McCarthy and Zakrajsek, 2007; Irvine and Schuh, 2005; McMahon and Wanengkirtyo, 2015). 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. 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. My model is similar though I introduce an endogenous JIT adoption decision and analyze a shock to fixed order costs rather than an aggregate productivity shock. Another related paper is Alessandria et al. (2023), which develops a rich two-country general equilibrium model and studies unexpected shocks to domestic and international shipping delays. I focus on analyzing the firm-level JIT adoption decision and its implications in a closed-economy model. The fixed order cost shock that I study encompasses shipping delays among other factors that may shift the probability of placing and receiving an order.

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. Nakamura et al. (1998) and Roumiantsev and Netessine (2008) find similar evidence. 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 a literature that studies JIT and supply chain disruptions. My empirical results align with Pisch (2020) which also finds that JIT adoption is associated with higher firm sales and sales per worker. In addition, my finding that JIT producers are more exposed to supply disruptions is consistent with Cajal-Grossi et al. (2023) which analyzes buyers' sourcing strategies in the garment industry and finds that JIT buyers suffered relatively larger declines in overall imported values amid the COVID-19 pandemic. Keane and Feinberg (2006) and Keane and

Feinberg (2007) document a strong correlation between JIT adoption and the increase in intra-firm trade in the 1980s and 1990s, and associate JIT with lower inventory carrying costs. Consistent with their findings, my measure of JIT adoption implies that the share of JIT producers increased substantially over this same period. In addition, my model implies that JIT producers, in equilibrium, experience lower inventory carrying costs than non-JIT producers. Other empirical work has assessed how shocks propagate through a network of firms (Barrot and Sauvagnat, 2016; Carvalho et al., 2021; Cachon et al., 2007).

From a theoretical perspective, my paper relates to models of heterogeneous firms, inventories, and supply chains. As previously noted, Alessandria et al. (2023) studies delays in a general equilibrium model. Evans and Harrigan (2005) rationalizes the shift in production away from lower-wage locations to higher-wage locations with a model of "lean retailing," which is akin to the notion of JIT in this paper. In the Evans and Harrigan (2005) model, lean retailing creates demand for timely delivery of orders, which is only met by producers that are geographically closer to their customer retailers. My model, which is applied to JIT manufacturers, also highlights the importance of timely, uninterrupted delivery for JIT, and the vulnerability of JIT to supply disruptions. Moreover, 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 and estimate the general equilibrium model of JIT production. I analyze the model in Section 5. Section 6 quantifies the aforementioned trade-off associated with JIT, and Section 7 concludes.

2 Empirical Patterns Among JIT Firms

I start by describing my approach to measuring JIT adoption. I then document empirical evidence indicating that JIT producers experience improved outcomes on average but are 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.

2.1 A New Measure of JIT Adoption

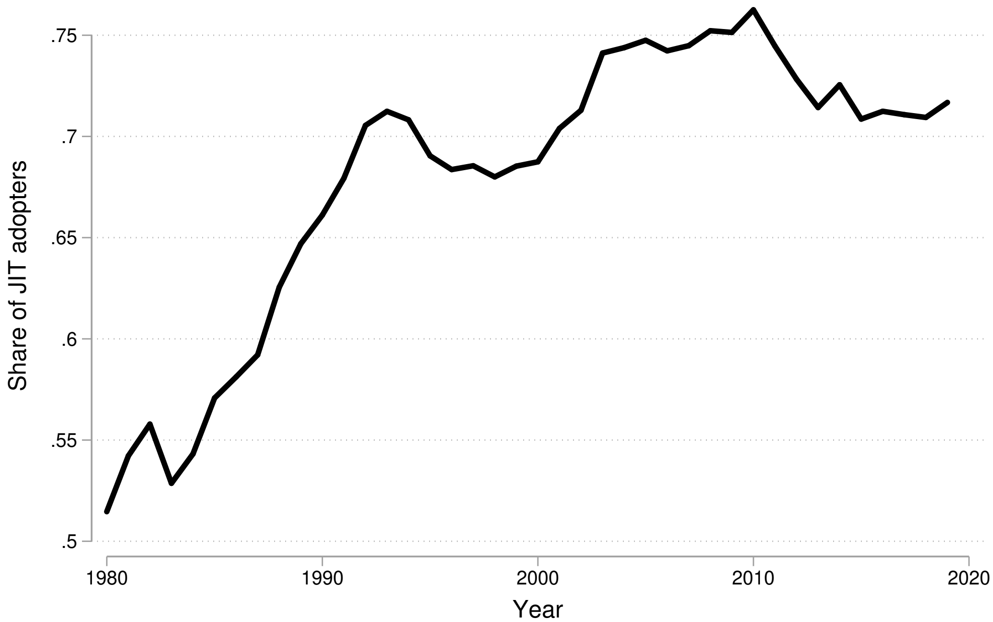
Ideally, one would measure JIT by observing which firms actually implement it. In practice, this is a challenging undertaking as firms may not always explicitly disclose their decision, or intention, to adopt JIT. However, since a hallmark of JIT is the commitment to reducing or eliminating inventories, it stands to reason that if we observe significant declines in inventory holdings among firms in an industry, then this must be due to the adoption of JIT or associated lean production strategies.

I therefore develop a measure of lean production among public manufacturers by comparing firm-level input inventory holdings to historical sector-level input inventory holdings. Formally, the JIT indicator for firm i belonging to two-digit NAICS sector j in year $t \geqslant 1980$ is defined as:

$$\text{JIT}_{ijt} = \begin{cases} 1 \text{ if } \frac{\text{Inventory}_{ijt}}{\text{Sales}_{ijt}} < \frac{\text{Inventory}_{j0}}{\text{Sales}_{j0}}, \\ 1 \text{ if } \frac{\text{Inventory}_{ijt}}{\text{Sales}_{ijt}} > \frac{\text{Inventory}_{j0}}{\text{Sales}_{j0}} \text{ and } \frac{\text{Inventory}_{ijt-1}}{\text{Sales}_{ijt-1}} < \frac{\text{Inventory}_{j0}}{\text{Sales}_{j0}} \text{ and } \frac{\text{Inventory}_{ijt+1}}{\text{Sales}_{ijt+1}} < \frac{\text{Inventory}_{j0}}{\text{Sales}_{j0}}, \\ 0 \text{ otherwise.} \end{cases} \tag{1}$$

where $\frac{\text{Inventory}_{j0}}{\text{Sales}_{j0}}$ denotes the median inventory-to-sales ratio across firms i in sector j over 1971 through 1979. In each year from 1980 to 2019, (1) defines a lean producer as a firm whose inventory-to-sales ratio is below the pre-1980 sector median, or whose inventory-to-sales ratio in years $t-1$ and $t+1$ are below the pre-1980 sector median even if its inventory-to-sales ratio in t is above the pre-1980 sector median. The latter condition allows my measure to better capture the persistence

Figure 1: Share of JIT Adoption



Note: The figure plots the measured share of firms that adopted JIT over time according to (1).

associated with the adoption of JIT.

When constructing my measure of JIT, I define "inventories" as input inventories which is the sum of raw material and works-in-process inventories. I do so because JIT is sometimes described as an input inventory concept and its effects appear to be particularly salient for input inventories. For instance, according to Calvasina et al. (1989) "JIT is a system of production control that seeks to minimize raw material and work-in-process (WIP) inventories..." In addition, Fullerton and McWatters (2001) find a statistically significant decrease in raw materials and work-in-process inventories among firms that adopt JIT but find little difference in finished goods inventories. Thus, my measure assumes that JIT adoption is more easily detected by inspecting the behavior of raw materials and works-in-process inventory holdings rather than finished goods inventory holdings. Moreover, I measure sector-level historical inventory-to-sales ratios by taking the median within sectors. I do this because the median is less sensitive to outliers than the mean.

Figure 1 plots the share of JIT producers over time based on (1). This measure implies that the share of firms engaging in JIT production trended up through the 1980s and part of the 1990s. My measure of JIT is agnostic about the forces leading to JIT adoption which could include improvements in transportation and logistics that made it feasible for more firms to arrange for small and frequent delivery of materials, improvements in information technology which allowed firms to better communicate with suppliers and more accurately forecast demand, and a new cohort of managers trained in JIT best practices.

Around the mid 1990s, the share of adoption continued to increase, though at a slower pace, and peaked around 2010. The leveling off in the share of JIT adopters observed from the mid-to-late 2000s could be attributed to uncertainty during the Great Recession, which perhaps activated precautionary inventory holding motives, or due to the formation of intricate and geographically vast supply chains which may have resulted in longer lead times (Carreras-Valle, 2024). Over the 2010s, the share of JIT firms declined slightly though remained at above 70% in my sample.

Others in the literature have measured JIT using survey data. For instance, Fullerton and McWatters (2001) conducts a survey of about 250 U.S. manufacturing firms and measures the share of JIT adopters to be 37.5%. In addition, Pisch (2020) observes JIT adoption using French firm level survey data and measures the share of French JIT manufacturers to be about 43% in 2006.

In Appendix A.2, I examine the robustness of my measure of JIT to alternative assumptions. In addition, I study the JIT adoption decision among a narrower set of manufacturing firms whose decision to adopt JIT is identified based on public announcements (Kinney and Wempe, 2002). Using this text-based definition of JIT, I verify that inventory-to-sales ratios decline within the firm following the adoption of JIT. Furthermore, I show that JIT producers in this narrower set of firms experience declines in inventory-to-sales ratios relative to their pre-1980s industry medians.

2.2 Empirical Facts Relating to JIT

I use my measure of JIT adoption along with other firm-level balance sheet information from Compustat Fundamentals Annual data over the aforementioned years to examine differences in outcomes between JIT and non-JIT firms. To study exposure to supply chain pressures, I merge my sample

Table 1: JIT Adoption and Firm Performance

	Sales	Sales per worker	Earnings
JIT	0.305***	0.279***	0.546***
	(0.015)	(0.014)	(0.050)
Fixed effects	Firm, Sector × Year	Firm, Sector × Year	Firm, Sector × Year
Firms	5,427	5,427	5,427
Observations	55,592	55,592	55,592

Note: The table reports panel regression results based on regression (2). The dependent variables are log sales, log sales per worker, and the inverse hyperbolic sine of earnings. Earnings are defined as income before extraordinary items. The control variables specified are firm age in the sample and log total assets. Two-digit NAICS codes are specified in the sector-by-year fixed effects. Standard errors are double clustered at the firm and fiscal year levels. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

with the GSCPI. My final sample consists of an unbalanced panel of over 5,000 unique manufacturing firms spanning the years 1980 to 2019. Appendix A.1 reports summary statistics of the firm-level variables in my sample.

I document three sets of facts about JIT adopters. First, JIT adoption is associated with higher sales, higher sales per worker, and higher earnings, the latter of which is measured as operating income. I estimate regressions of the following form:

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

where y_{ijt} is an outcome variable for firm i belonging to sector j in year t. The regressor of interest, JIT_{ijt}, is the time-varying JIT adoption indicator, defined in equation (1). I control for firm age in the sample and the log of total assets, and specify firm and sector-by-year fixed effects in these regressions. Table 1 reports the regression results. The first column implies that JIT adoption is associated with a roughly 30% increase in sales. In addition, JIT adoption is associated with a 28% increase in sales per worker and a 55% increase in earnings. The results imply changes of 13%, 32%, and 17% of one standard deviation in the outcomes, respectively.

The results reported in Table 1 are consistent with those documented in the operations manage-

Table 2: JIT Adoption and Firm Volatility

	Sales growth volatility	Employment growth volatility	Earnings growth volatility
JIT	-0.190***	-0.047*	-0.116**
	(0.028)	(0.024)	(0.047)
Fixed effects	Sector × Year	Sector × Year	Sector × Year
Firms	2,800	2,796	2,800
Observations	18.975	18,903	18,955

Note: The table reports panel regression results based on regression (3). The dependent variables are rolling five-year standard deviations of firm sales growth, employment growth, and earnings growth. Lagged log of total assets and age in sample are specified as controls. Two-digit NAICS codes are specified in the sector-by-year fixed effects. Standard errors are double clustered at the firm and fiscal year levels. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

ment literature. For example, Fullerton and McWatters (2001) finds that 61.5% of self-reported JIT adopters observed improved profitability following the adoption of JIT. Using cross-country survey data covering about 160 plants in the electronic, machinery, and transportation parts and supplier industries, Cua et al. (2001) documents evidence suggesting that JIT adoption leads to improvements in firm performance particularly when implemented alongside total quality management and total productive maintenance, which constitute other manufacturing strategies. The results in Table 1 are also similar to Pisch (2020) which finds that JIT producers are characterized by higher sales, sales per worker, and lower inventory holdings. Whereas I measure JIT by observing changes in inventory-to-sales ratios rather than through survey responses, I draw similar conclusions to related studies.

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

$$y_{ijt} = \gamma \mathrm{JIT}_{ijt} + \mathbf{X}'_{ijt}\beta + \delta_{jt} + \eta_{ijt}, \tag{3}$$

where y_{ijt} denotes rolling 5-year standard deviations of sales, employment, and earnings growth for firm i in sector j in year t. Table 2 reports the results. JIT adoption is associated with a roughly 19%, 5%, and 12% decline in sales growth volatility, employment growth volatility, and earnings

Table 3: JIT Adoption and Supply Chain Pressures

	(1) Sales	(2) Sales
Supply chain pressure	0.012	
	(0.012)	
Supply chain pressure × JIT	-0.023**	-0.022**
	(0.009)	(0.009)
Fixed effects	Firm	Firm, Sector × Year
Firms	2,766	2,766
Observations	20,608	20,608

Note: The table reports panel regression results from regression (4). The dependent variable is the log of firm sales. Lagged log of total assets, employment, and finished goods are specified as controls as well as firm age and contemporaneous unemployment rate, real GDP growth, and manufacturing PPI inflation. Two-digit NAICS codes are specified in the sector-by-year fixed effects. Standard errors are double clustered at the firm and fiscal year levels. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

growth volatility, respectively. The lower estimated volatility following JIT adoption is a novel empirical finding not previously documented in the literature.

Third, JIT adopters tend to be more sensitive to aggregate supply pressures. I merge my data with the GSCPI and estimate regressions that interact adoption with supply chain pressures. 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 supply chain pressures rise. I therefore estimate the following regression:

$$y_{ijt} = \gamma_1 \text{JIT}_{ijt-1} + \gamma_2 \text{GSCPI}_t + \gamma_3 \big[\text{JIT}_{ijt-1} \times \text{GSCPI}_t\big] + \mathbf{X}'_{ijt}\beta + \text{FE} + \varepsilon_{ijt}, \tag{4}$$

where GSCPI denotes the global supply chain pressure index, which I standardize, and $\mathbf{X}$ reflects a set of controls. The coefficient γ_3 measures the extent to which JIT firms exhibit more or less sensitivity to increases in supply chain pressures.

Table 3 builds on previous studies estimating the exposure of JIT production to supply disruptions (Cajal-Grossi et al., 2023) by providing estimates of the exposure of JIT firms to the GSCPI. Based on column (1), a one standard deviation increase in the supply chain pressure index is associated with a roughly 2.3% stronger decline in sales among JIT firms. Turning to column (2), when controlling for sector-by-year fixed effects, which subsumes the second term of equation (4), I find that the magnitude of the excess sensitivity of JIT firms is similar, implying that JIT firm sales decline by about 2.2% more than non-JIT firms. In Appendix A.3, I show that this exposure also appears to be present when JIT firms' suppliers face adverse weather events.

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. My model of heterogeneous firms with inventories, fixed ordering costs, and an endogenous JIT adoption decision can explain these 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 JIT Production

Having illustrated the essence of the trade-off in the data, I next build a dynamic 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).

3.1 Representative Household

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:

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

where $\phi > 0$ denotes the household's labor disutility. Total hours worked is denoted by H_t and labor is paid wage, w_t, which the household takes as given. 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:

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

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. Optimization implies the following,

$$w_t = \phi C_t \tag{5}$$

$$1 = \beta R_{t+1} \frac{C_t}{C_{t+1}} \tag{6}$$

where (5) is the labor supply optimality condition and (6) is the intertemporal Euler equation, where the stochastic discount factor, Λ_{t+1}, is defined as $\Lambda_{t+1} = \beta \frac{C_t}{C_{t+1}}$.

3.2 Representative Intermediate Goods Producer

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.

3.3 Heterogeneous Final Goods Producers

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

$$y_{it} = z_{it} m_{it}^{\theta_m} n_{it}^{\theta_n}, \quad \theta_n + \theta_m < 1,$$

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

$$\log(z_{it+1}) = \rho_z \log(z_{it}) + \sigma_z \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0, 1).$$

Materials are drawn from the firm's existing inventory stock, s_{it}, 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.

Each period consists of three stages. A producer, i, enters the period with realized productivity, z_{it}, inventory stock, s_{it}, and adoption status, a_{it}. In the first stage, the producer decides whether or not to adopt JIT. If a producer does not enter the period as a continuing adopter, it must pay c_s in order to adopt JIT. Alternatively, if the producer enters the period as an adopter of JIT, 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, c_s, encompasses all of these one-time costs. The continuation cost, c_f, 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_{it}, its target inventory stock is denoted by s^*_{it}. This means that any orders, if placed, are defined as $o_{it} = s^*_{it} - s_{it}$. Following the order decision, suppose that inventory stock $\widetilde{s}_{it}$ is carried into the production stage such that $\widetilde{s} = s$ if no order is placed and $\widetilde{s} = s^*$ if an order is placed. Materials used in production are then defined as $m_{it} = \widetilde{s}_{it} - s_{it+1}$ where s_{it+1} refers to the inventory stock carried forward into the next period.

3.4 Recursive Formulation of Final Goods Producers' Problem

In the recursive formulation of the final goods firm problem that follows, I suppress time subscripts 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, w and q, where w is the wage, q is the price of intermediate goods. The firm first decides whether to adopt JIT. Noting that JIT adoption is a binary outcome, the value of adopting is:

$$V^A(z,s,a) = \max\Bigg\{ - wc(a) + \int V^O(z,s,1,\xi)dF(\xi_A), \int V^O(z,s,0,\xi)dF(\xi_{NA})\Bigg\}, \tag{7}$$

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: $F(\xi) = U(\underline{\xi}, \overline{\xi})$.[5] The firm's optimal adoption policy, $a'(z,s,a)$, solves (7).

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. The value in the second stage is

$$V^O(z,s,a,\xi) = \max\Bigg\{ - w\xi + V^*(z,s,a), V^P(z,s,a)\Bigg\}, \tag{8}$$

where the value of placing an order is[6]

$$V^*(z,s,a) = \max_{s^* \geqslant s}\Bigg[- q(s^*-s) + V^P(z,s^*,a)\Bigg], \tag{9}$$

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

$$\xi^*(z,s,a) = \min\Big(\max\big(\underline{\xi}, \tilde{\xi}(z,s,a)\big), \overline{\xi}\Big), \tag{10}$$

[5]As in Khan and Thomas (2007), I assume uniformly distributed order costs. In my 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.

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

and

$$\widetilde{\xi}(z,s,a) = \frac{V^*(z,s,a) - V^P(z,s,a)}{w}. \tag{11}$$

Stage 3: Production Decision

Next, production takes place. Suppose that a firm enters the production stage with inventory stock $\widetilde{s}$ such that:

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

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:

$$V^P(z,\widetilde{s},a) = \max_{s' \in [0,\widetilde{s}]} \pi(z,\widetilde{s},s',a) + \mathbb{E}\big[\Lambda' V^A(z',s',a')\big] \tag{12}$$

where

$$\pi(z,\widetilde{s},s',a) = zn(z,\widetilde{s},s',a)^{\theta_n}(\widetilde{s} - s')^{\theta_m} - wn(z,\widetilde{s},s',a) - c_m s' \tag{13}$$

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

3.5 Equilibrium

An equilibrium is a set of decision rules, $\{s^*(z,s,a), s'(z,s,a), \xi^*(z,s,a), a'(z,s,a), n(z,s,a), y(z,s,a)\}$, value functions, $\{V^A(z,s,a), V^O(z,s,a), V^*(z,s,a), V^P(z,s,a)\}$, measure of firms $\mu(z,s,a)$, prices, $\{w,q,\Lambda\}$, and quantities $\{C,H,K,L\}$ such that:

1. The representative household's first order conditions, (5) and (6), hold.

2. The intermediate goods firm first order conditions hold:

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

3. The value function and decision rules solve the final goods firms' problem.

4. All markets clear.

   The final goods market clearing condition is:

$$
\begin{aligned}
C = & \int\int y(z, s^*(z,s,a), s'(z,s,a), a, \xi) dF(\xi^*(z,s,a)) d\mu(z,s,a) \\
& + \int\int y(z, s, s'(z,s,a), a, \xi)[1 - dF(\xi^*(z,s,a))] d\mu(z,s,a) \\
& - c_m \Bigg(\int\int s'(z, s^*, a) dF(\xi^*(z,s,a)) d\mu(z,s,a) \\
& + \int\int s'(z,s,a)[1 - dF(\xi^*(z,s,a))] d\mu(z,s,a) \Bigg) - K.
\end{aligned}
$$

   The intermediate goods market clearing condition is:

$$
K^\alpha L^{1-\alpha} = \int\int [s^*(z,s,a) - s] dF(\xi^*(z,s,a)) d\mu(z,s,a).
$$

   The labor market clearing condition is:

$$
\begin{aligned}
H = & \int\int n(z, s^*(z,s,a), s'(z,s,a), \xi) dF(\xi^*(z,s,a)) d\mu(z,s,a) \\
& + \int\int n(z, s, s'(z,s,a), a, \xi)[1 - dF(\xi^*(z,s,a))] d\mu(z,s,a) \\
& + \int \left[\int_0^{\xi^*(z,s,a)} \xi dF(\xi) \right] d\mu(z,s,a) + \int a'(z,s,a)[(1-a)c_s + ac_f] d\mu(z,s,a) + L.
\end{aligned}
$$

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

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

   where

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

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

4 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 inventories and sales as well as the share of JIT adoption and mode switching.

4.1 Simulated Method of Moments

There are 14 parameters in the model. I externally fix seven parameters which are detailed in Panel A of Table 4. The discount factor, β, is set to be consistent with an annual 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 0.65. The leisure preference is calibrated so that the household works for one-third of total hours. Finally, I set the order cost lower bounds to zero for both JIT adopters and non-adopters.

I estimate the remaining seven parameters. The parameter vector to be estimated is

$$\theta = \begin{pmatrix} \rho_z & \sigma_z & \overline{\xi}_{NA} & \overline{\xi}_A & c_s & c_f & c_m \end{pmatrix}'.$$

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.3. To estimate the model, I employ SMM (Duffie and Singleton, 1993; Bazdresch et al., 2018).

Specifically, I target 10 moments to estimate the seven parameters. My estimator is therefore an overidentified SMM estimator. Of the ten moments, four are specific to JIT firms and four to non-JIT firms. These four moments, which are the same across both types of firms, are: the mean

Table 4: Model Parameterization

Panel A: External Calibration			
Description	Parameter	Value	
Discount Factor	β	0.962	
Labor disutility	ϕ	2.450	
Material share	θ_m	0.520	
Labor share	θ_n	0.280	
Capital share	α	0.390	
Order cost lower bound (non-JIT)	$\underline{\xi}_{NA}$	0.000	
Order cost lower bound (JIT)	$\underline{\xi}_{A}$	0.000	
Panel B: Internally Estimated			
Description	Parameter	Estimate	Standard error
Productivity shock persistence	ρ_z	0.588	0.0007
Productivity shock dispersion	σ_z	0.118	0.0002
Order cost upper bound (non-JIT)	$\overline{\xi}_{NA}$	3.418	0.0076
Order cost upper bound (JIT)	$\overline{\xi}_{A}$	0.311	0.0002
Sunk cost of adoption	c_s	0.783	0.0025
Continuation cost of adoption	c_f	0.072	0.0001
Carrying cost	c_m	0.230	0.0001

Note: Panel A reports the seven calibrated model parameters. Panel B reports the seven internally estimated parameters, which are estimated by targeting the 10 moments in Panel A of Table 5.

inventory-to-sales ratio and the covariance matrix of log sales and log inventories, the latter of which delivers three moments. The final two moments are the observed share of JIT adoption and the share of firms switching out of JIT.[7] I specify the asymptotically efficient weighting matrix which is the inverse of the covariance matrix of the moments. Appendix C.2 discusses the relationships between the moments and parameters and provides some intuition behind the identification of the model parameters.

Panel B of Table 4 reports the estimated baseline model parameters, all of which are precisely estimated.[8] 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).

[7] The empirical moments are listed in Panel A of Table 5.

[8] A test of overidentifying restrictions delivers a J-statistic of 5.28 with a p-value of 0.15 for the baseline model. As a result, I fail to reject that the baseline model is misspecified, lending further support to the validity of the estimates.

The upper support of the order cost distribution among non-adopters is about 3.4 while the upper bound of order costs for JIT adopters is 0.31. The average fixed order costs implied by these estimates account for about 15% and 11% of the total cost placing an order for non-JIT and JIT firms, respectively. Furthermore, the adoption cost estimates suggest a meaningful amount of persistence in the adoption decision. Conditional on being an adopter, the probability of remaining an adopter is 92%. For reference, this estimate is slightly higher 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 inventory carrying costs are about 2.5% of value added, a non-negligible amount that prevents firms from carrying too many inventories across time.

4.2 Model Fit

Panel A of Table 5 shows that the model is broadly successful in fitting the targeted empirical moments. The model is able to reproduce lower average inventory-to-sales ratios and empirically relevant shares of adoption and mode switching. The estimated model also matches the covariance matrices of sales and inventories fairly well.

To further assess the baseline model's ability to match the patterns present in the data, I estimate the empirical regressions reported in Tables 1 and 2 based on a panel of simulated firms from the estimated baseline model.[9] The results are reported in Panel B of Table 5.

In the baseline model, JIT adoption is associated with a 36% increase in sales, similar to the 31% increase estimated in the data. The model also predicts an increase in earnings following adoption, however the magnitude is smaller than in the data. Furthermore, the baseline model predicts reductions in firm sales volatility of 19% and a 37% decline in earnings growth volatility among JIT firms, relative to 18% and 12% declines estimated in the data, respectively.

Two forces in the model govern the degree of micro volatility among JIT producers relative

[9] Because the model abstracts away from an extensive margin of employment, I do not report model-based estimates for output per worker or employment growth volatility.

Table 5: Model Fit to Data Moments

Panel A: Targeted Moments		
Moment	Model	Data
Mean(inventory-sales ratio|non-JIT)	0.226	0.285
		(0.005)
Mean(inventory-sales ratio|JIT)	0.081	0.073
		(0.001)
Var(log sales |non-JIT)	0.475	0.481
		(0.015)
Cov(log sales, log inventories|non-JIT)	0.365	0.308
		(0.012)
Var(log inventories|non-JIT)	0.357	0.402
		(0.013)
Var(log sales |JIT)	0.340	0.314
		(0.008)
Cov(log sales, log inventories|JIT)	0.175	0.244
		(0.007)
Var(log inventories|JIT)	0.462	0.430
		(0.010)
Share of JIT adopters	0.676	0.676
		(0.010)
Share switching out of JIT	0.081	0.037
		(0.001)
Panel B: Non-targeted regression coefficients		
	Model	Data
Sales on JIT	0.364	0.305
	(0.007)	(0.015)
Sales on Earnings	0.317	0.546
	(0.006)	0.050)
Sales growth volatility on JIT	-0.185	-0.180
	(0.002)	(0.029)
Earnings growth volatility on JIT	-0.374	-0.116
	(0.004)	(0.047)

Note: Panel A reports model-based and empirical moments along with standard errors of the empirical moments. Panel B reports model-based and empirical regression coefficients with standard deviations and standard errors in parentheses.

to non-JIT producers. First, JIT producers are more sensitive to fluctuations in idiosyncratic productivity realizations compared to non-JIT producers. Second, JIT adopters face less variable fixed ordering costs. In the estimated model, the latter effect is quantitatively stronger, allowing JIT firms to smooth their ordering cycles, implying less sales and earnings growth volatility relative to non-JIT firms. With precisely estimated parameters delivering a broadly successful fit to targeted and non-targeted moments in the data, I next use the estimated model to analyze optimal firm decisions.

5 Analyzing Optimal Firm Decisions

The endogenous adoption decision allows the model to replicate important features of the data, namely, higher profitability and reduced micro volatility among JIT firms. A finished goods producer in the model chooses to adopt JIT if the expected benefit of doing so exceeds the cost. From the producer's recursive problem, we can express the condition for adopting JIT as,

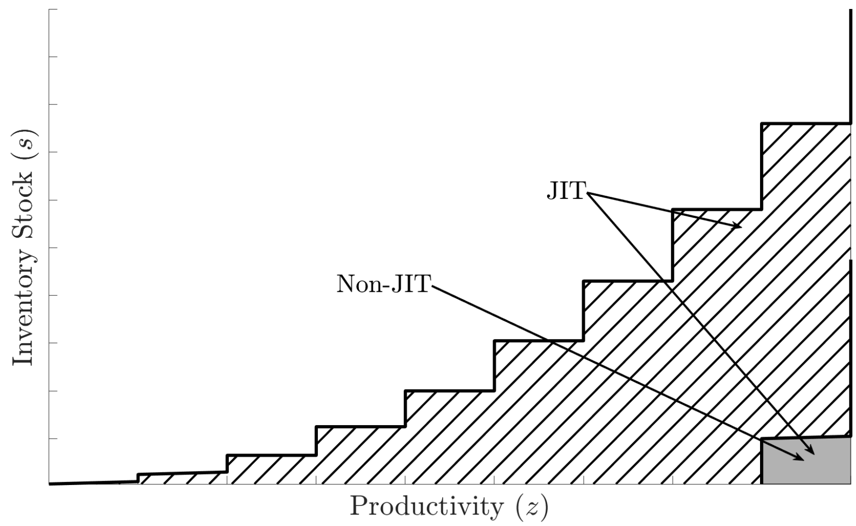
$$\frac{\int V^O(z,s,1,\xi)dF(\xi_A) - \int V^O(z,s,0,\xi)dF(\xi_{NA})}{w} \geqslant c(a) \tag{14}$$

where the left hand side of (14) reflects the expected benefit of adopting JIT and the right hand side is the cost of adopting JIT. A firm adopts JIT if and only if the benefit of doing so exceeds the cost.

Since implementing JIT comes at a relatively large initial cost, not all firms optimally choose to adopt JIT. Figure 2 plots the adoption frontiers of the estimated model 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 producers 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 those 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, c_f, is smaller than the initial sunk cost, c_s. Hence, the endogenous adoption decision exhibits persistence. The additional striped area in Figure 2 reflects this intuition. Only the least productive adopters abandon JIT. Furthermore, the scope

Figure 2: Adoption Frontiers



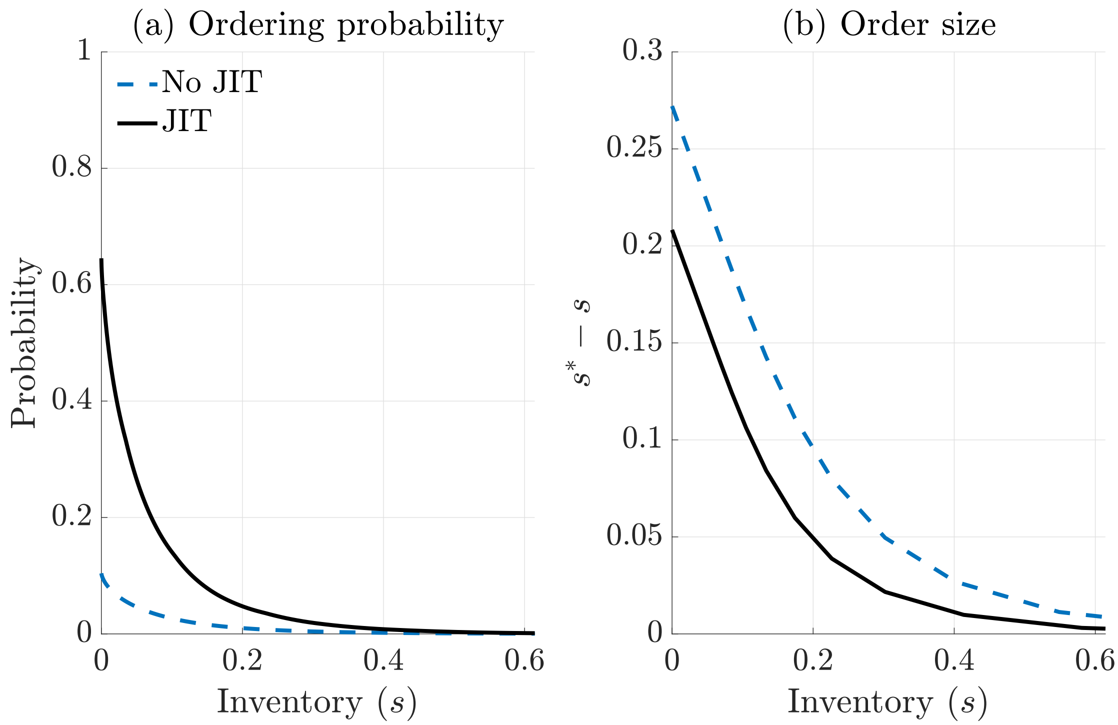
Note: The figure plots adoption frontiers for JIT and non-JIT producers. The solid gray area depicts the region of the state space in which non-JIT producers select into adoption. The striped area and the gray area jointly denote the region of the state space in which existing JIT producers choose to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

for exiting adoption is increasing in inventory holdings.

Other costs in the model also affect the incentives to adopt JIT. For instance, all else equal, an increase in inventory carrying costs expands the JIT adoption frontiers in Figure 2 as JIT allows firms to be less burdened by higher carrying costs since they optimally hold fewer inventories across time. If, however, the cost of maintaining JIT is sufficiently high, then firms may choose to forego JIT adoption even with large storage costs since the cost of maintaining JIT would exceed the benefit of optimally holding fewer inventories and in turn incurring a smaller carrying cost.

I next examine the optimal ordering decisions based on the estimated model. Panel (a) of Figure 3 shows the probability of placing an order as a function of inventories for JIT and non-JIT producers, averaging over idiosyncratic productivity. At all inventory levels, the probability of placing an order is higher for JIT adopters since they face lower average order costs. Furthermore, Panel (b) of Figure 3 plots the optimal order size for JIT and non-JIT producers. Order sizes among JIT firms are lower than those of non-JIT firms because the former face lower average fixed order costs.

Figure 3: Ordering Decisions



Note: The left panel plots the probability of placing an order as a function of inventories, averaging over idiosyncratic productivity. The right panel plots the order size as a function of inventories, averaging over idiosyncratic productivity.

Taken together, these panels imply that, facing lower fixed order costs, adopters will hold fewer inventories in favor of placing smaller more frequent orders. Upon shrinking their inventory stocks, adopters also incur smaller carrying costs. These cost reductions enable JIT firms to allocate more resources to production, allowing them to generate more sales. Furthermore, due to the lower and less variable fixed ordering costs, firms are able to more easily time their orders and can smooth out their ordering cycles which moderates the variability of other firm-level outcomes as well.

6 Quantifying the Aggregate Effects of JIT

I next quantify the aggregate effects of the firm-level decision to adopt JIT. I begin by highlighting the vulnerability to unanticipated supply disruptions engendered by JIT. I then explore the aggregate implications of transitioning from a lean economy to a more "resilient" economy that features less JIT and larger inventory stocks.

A natural benchmark against which to compare the estimated model is a world in which JIT adoption is not possible. I define such a counterfactual by solving a version of the estimated model with adoption cost parameters c_s and c_f fixed to be prohibitively large such that no adoption takes place.

6.1 Effects of an Unanticipated Supply Disruption

From the perspective of the model, the benefits associated with JIT come in the form of higher long-run output and less firm-level volatility. Comparing the steady states of the baseline JIT economy and the no JIT counterfactual economy, I find that aggregate output in the JIT economy is about 15% higher than in the no JIT economy.

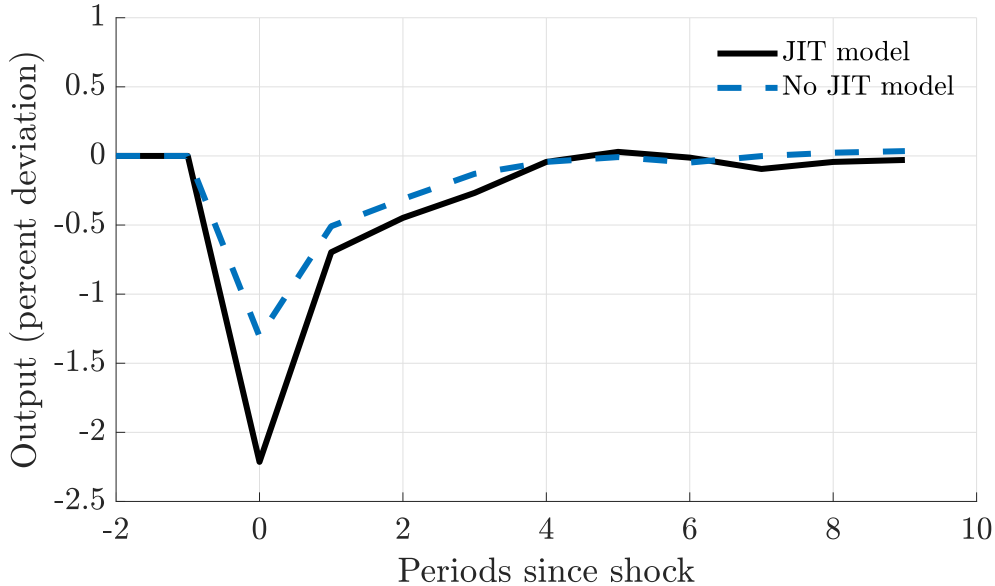
Despite the benefits associated with JIT adoption, the baseline JIT economy is more vulnerable to an unexpected aggregate supply disruption. To quantify this vulnerability, I consider an unanticipated increase in economy-wide fixed order costs and assume that it evolves deterministically according to $\zeta_{t+1} = \rho_\zeta^\xi \zeta_t$ where $\rho_\zeta^\xi = 0.50$ and $\zeta_0 > 0$. This shock shifts the average fixed order cost distribution of JIT and non-JIT producers:

$$\underline{\xi}_t = \underline{\xi} + \zeta_t \quad \text{and} \quad \overline{\xi}_t = \overline{\xi} + \zeta_t.$$

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 4 displays the output response to this unexpected shock. The JIT economy sees a roughly one percentage point excess output contraction on impact. The total output loss in the JIT economy along the transition back to steady state is 3.8% while it is 2.3% in the counterfactual economy. Given the sizable 15% pre-shock output gains in the JIT economy, this exercise implies that, overall, JIT likely remains a beneficial strategy for firms to pursue in the long run. In Appendix D.2, I

Figure 4: Sharper Contraction to Supply Disruption with JIT



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.

conduct a similar exercise for smaller and larger-sized shocks.

Amid the supply disruption, order-placing probabilities decline more in the baseline model relative to the counterfactual model. 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 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 model. Since inventory investment is 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:

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

the excess output contraction in the baseline model comes from both a relatively stronger decline in final sales and a stronger fall in inventory investment.[10]

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 disruption. The excess output loss amounts to about $310 billion, a figure comparable to the funds appropriated for economic impact payments to individuals amid the pandemic.[11] 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.

6.2 Transition to "Resilience"

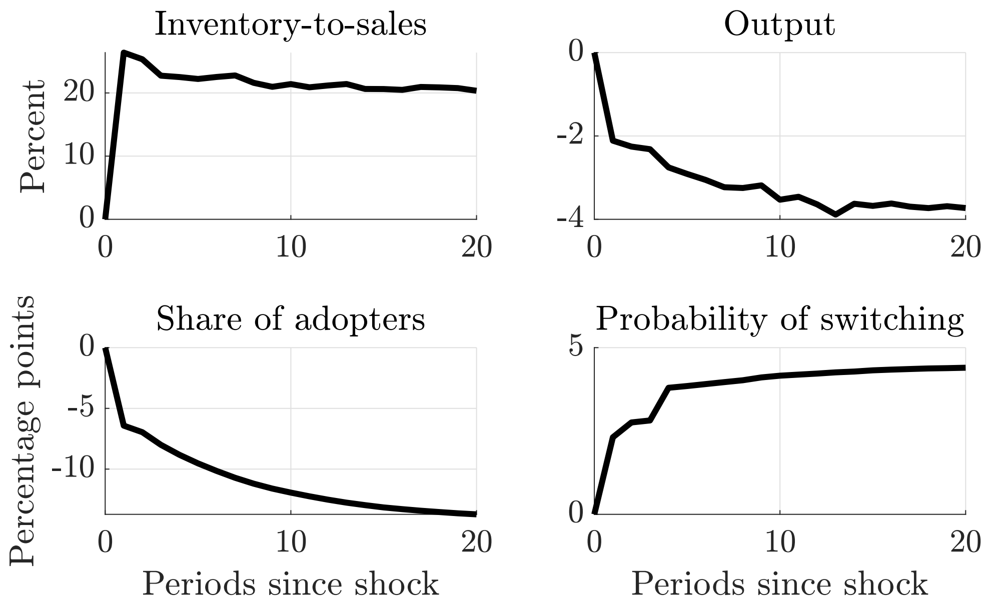
Finally, I examine how the JIT economy would transition to a new normal that features higher fixed ordering costs. A new steady state with higher fixed ordering costs is intended to capture a greater risk of supply disruptions such as those experienced in recent years amid the COVID-19 pandemic, heightened geopolitical risks, and trade policy uncertainty. In this new equilibrium, some firms will have abandoned JIT. A prominent real-world example of a firm which moved away from lean inventories is Toyota following the Fukushima earthquake.

I consider an increase in economy-wide fixed order costs that generates a 20% increase in the inventory-to-sales ratio, consistent with the increase observed in an extended version of my sample when comparing the average 2024 inventory-to-sales ratio to the average 2019 inventory-to-sales ratio. Figure 5 plots four panels which illustrate the transition from the lean steady state to the new, higher inventory steady state. The top left panel traces out the transition to an equilibrium in which inventory-to-sales rise by 20%. The right panel shows that output declines over time and falls by almost 4% in the new steady state. In addition, along the transition the share of JIT adoption gradually declines and ultimately falls by about 14 percentage points. Meanwhile, the

[10] In the data, real final sales of domestic product declined by 1.7% in 2020. In the model, real sales decline by 2% amid the shock.

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

Figure 5: Transition to Higher Inventory Steady State



Note: The figure plots the transition of various endogenous outcomes to a new steady state that features a higher level of inventories.

probability of switching out of JIT rises by about 4.5 percentage points. Moreover, consumption-equivalent welfare declines by -0.72%. This exercise quantifies the potential costs associated with transitioning to a higher inventory steady state. A deeper analysis of the possible sources of more frequent supply disruptions after the COVID-19 pandemic, and an exploration of the incentives to abandon JIT, is beyond the scope of this paper and would be a fruitful avenue for future research.

7 Conclusion

In normal times, 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 particularly susceptible to aggregate supply disruptions. In a model of JIT production, firms that adopt JIT enjoy an increase in earnings and experience less unconditional micro volatility. At the same time, JIT elevates firm vulnerability to supply disruptions due to low inventory buffers. With that said, transiting to an equilibrium with higher inventory buffers is costly. Overall, JIT adoption gives rise to an important trade-off 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 pay close attention to inventories and inventory management practices.

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