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 finds that JIT creates a trade-off between firm profitability and vulnerability to large shocks. Empirically, JIT adopters experience higher sales and less volatility while also exhibiting heightened cyclicality and sensitivity to natural disasters. I explain these facts in a structurally estimated general equilibrium model where firms can adopt JIT. Relative to a no-JIT economy, the estimated model implies a 1.3% increase in firm value. At the same time, an unanticipated shock results in a roughly 15% deeper output contraction. This occurs because firms "stock out" or hoard materials.

Keywords: Inventory investment. Firm dynamics. Just-in-time production.
JEL Codes: D25, E22, G30

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1 Introduction

In the United States, 70% of manufacturers use just-in-time (JIT) production, a lean inventory management philosophy that aims to minimize the time between orders.[1] JIT grew in popularity beginning in the early 1980s as firms adopted technologies and practices that allowed them to cut costs associated with managing large material purchases and storing idle stocks. Instead these firms committed to placing smaller and more frequent orders from their suppliers.[2] Consequently, lean inventory management is believed to have contributed to the 35% reduction in the aggregate inventory-to-sales ratio between 1980 and 2018.[3] Moreover, many commentators and academics have pointed to leaner inventory management practices as one of the reasons for the decline in volatility of several macroeconomic aggregates that took place beginning in the 1980s (McConnell and Perez-Quiros, 2000; Blanchard and Simon, 2001; Kahn et al., 2002).

This paper offers a new perspective on the role of lean inventories in driving aggregate fluctuations, finding that it can create macro fragility in the face of unexpected shocks such as COVID-19. I document evidence of a trade-off from a novel dataset of JIT firms and quantitatively assess the role that lean production plays at the micro and macro levels in a structurally estimated heterogeneous firms model.

I begin by developing an indicator of the adoption of JIT for approximately 200 publicly listed manufacturing firms. Using narrative records from SEC filings and historical archives, I construct an adoption dummy that measures the year when the firm adopted JIT. I then link the measure of JIT to firm-level balance sheet data and document stylized facts relating to JIT proudcucers. First, I show that JIT adoption is associated with a 13% decrease in inventory-to-sales ratios and a 9% increase in sales. In addition, JIT firms experience a 7% decline in employment and sales growth volatility. 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 first 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.

adoption 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 exposed to the business cycle and other unexpected aggregate events. At the firm level, sales growth among JIT firms comoves more closely with GDP growth than their non-JIT counterparts. JIT firms are estimated to be between 25-30% more cyclical than non-JIT firms. In addition, JIT adopters experience a 3% sharper drop in sales when faced with unexpected weather disasters. My analysis points to heightened sensitivity among JIT firms upon the realization of external 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 their idiosyncratic productivity, inventory holdings, and inventory management strategy. Materials are needed for production and 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 that 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 adoption status, whether to order materials, and how much to produce.

I numerically solve and structurally estimate the model via the simulated method of moments (SMM) based on data from 1980 through 2018. The estimated model successfully fits the targeted moments and is also able to produce non-targeted regression coefficients consistent with those estimated in the data. Relative to a counterfactual economy with no JIT, the estimated model yields a welfare gain of 1.4% in consumption equivalent terms.[4] In addition, the estimated model delivers a 1.3% 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 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, the existence of leaner firms

[4]This welfare figure is comparable though slightly lower than measures of gains from trade (Costinot and Rodriguez-Clare, 2015).

renders the economy more vulnerable to unexpected shocks. I consider an unanticipated supply disruption calibrated to match the drop in real US output during the onset of the COVID-19 pandemic. In response to such a shock, the JIT economy experiences: (1) a more gradual depletion of inventories, (2) a higher share of firms that face stockouts, and (3) an increase in the share of firms that do not adopt JIT. Since JIT firms carry fewer inventories, an unexpected spike in the price of orders makes them more likely to fully exhaust their existing stocks. At the same time, as order costs rise, inventories are suddenly more highly valued, with an increase in the shadow value of inventories within the firm. As a result, producers that do not fully stock out cut back on material input use in an effort to draw inventories down more slowly. The utilization of fewer material inputs in production in the JIT economy due to stockouts and hoarding leads to a sharper drop in output relative to the counterfactual model.

My empirical and theoretical analysis quantifies a novel trade-off between the higher profits afforded by JIT production and the higher volatility caused by a leaner inventory system. Firms may benefit in normal times from pursuing a lean inventory strategy, even though an unanticipated adverse shock may trigger a deeper crisis in an economy populated by a large share of JIT producers.

Inventory investment has long been of interest to economists as a potential source of macroeconomic volatility.[5] Seminal contributions developed production smoothing models (Ramey and Vine, 2004; Eichenbaum, 1984), stockout avoidance models (Kahn, 1987), and (S,s) models (Scarf, 1960; Caplin, 1985) of inventory investment. Khan and Thomas (2007) elegantly models inventories in a general equilibrium environment with heterogeneous firms and business cycle shocks. The authors find that inventories play little to no role in amplifying or dampening business cycles.[6] My model is similar with an endogenous JIT adoption decision that depends on the firm's productivity, and a focus on large unanticipated shocks. A trade-off emerges in my model because firms do not internalize the prospect of the large shock in their private decisions.[7]

[5] 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).

[6] Iacoviello et al. (2011) comes to a similar conclusion albeit through a different model. On the other hand, Wen (2011) builds a stockout avoidance model and finds that inventories are stabilizing.

[7] This result holds even when allowing for partial anticipation of the shock or the introduction of stockout costs.

In addition, this paper speaks to the inventory management literature. Kinney and Wempe (2002) finds that JIT adopters outperform non-adopters, primarily through profit margins. Nakamura et al. (1998) as well as Roumiantsev and Netessine (2008) find similar evidence. In a contribution to the corporate finance literature, Gao (2018) examines the role of JIT production in corporate cash hoarding. Moreover, in the trade context, Alessandria et al. (2010) study an economy featuring inventory management problems relating to delivery lags. My paper provides a bridge between the management literature on lean inventories and the rich literature on inventories in macroeconomics by highlighting how JIT production matters 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 disasters. Other empirical work has assessed how shocks propagate through a network of firms. For instance, Carvalho et al. (2021) does this in the context of the 2011 Japanese earthquake. 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. Meier (2020) models supply chain disruptions in the context of time to build. Moreover, I model the JIT adoption decision in a manner similar to Alessandria and Choi (2007) who model path dependent export decisions. My paper explicitly links supply chain disruptions to an important source of investment at the macro 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 trade-off associated with JIT, and Section 7 concludes.

2 Empirical Patterns Among JIT Firms

I first document empirical evidence indicating that JIT adopters are more efficient and yet are more exposed to external shocks. 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 gather firm-level information by making use of Compustat Fundamentals Annual data for firms from 1980-2018. I merge these data with information on county-level weather events from the National Oceanic and Atmospheric Administration (NOAA) with specific links from Barrot and Sauvagnat (2016). In addition, I develop a new measure of JIT adoption among publicly traded manufacturers by 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 mentioned in the announcements. In all, my dataset identifies the years in which approximately 200 Compustat manufacturers adopted JIT.[8] More than half of observed JIT producers adopt prior to 1990, and nearly all of the adopters in my sample adopt JIT before 2000. My final sample consists of an unbalanced panel of about five thousand unique manufacturing firms spanning the aforementioned time period. Appendix A provides summary statistics of the data, and it also corroborates the empirical results using an alternate measure of JIT based on structural breaks in inventory holdings.

Using these data, I document four facts about JIT adopters. First, JIT adoption is associated

[8] 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 not picked up in the text search and which are subsequently assigned as non-JIT firms). I account for this possibility when modeling JIT by incorporating a parameter that governs the observed frequency of adoption. Section 5 discusses this in further detail. Second, there could potentially be measurement error in the reported years of JIT adoption. Appendix A provides validating evidence of my JIT measure by demonstrating that inventory holdings decline precisely in the recorded year of adoption.

Table 1: JIT Adoption and Firm Profitability

	(1) Inventory-to-sales	(2) Sales
Adopter	-0.128***	0.090***
	(0.044)	(0.027)
Fixed effects	Firm, Industry × Year	Firm, Industry × Year
Firms	5,017	5,017
Observations	45,768	45,768

Note: The table reports panel regression results from Compustat Annual Fundamentals based on regression (1). The regressor of interest is the firm-year specific adoption indicator. Firm age in the sample is specified as a control variable. Four-digit SIC codes are specified in the industry-by-year fixed effects. Standard errors are clustered at the firm level. The standard deviations of the dependent variables are 0.82 and 2.21, respectively. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

with both lower inventory holdings and higher sales within firms.[9] I estimate:

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

where y_{ijt} is an outcome variable for firm i belonging to 4-digit SIC manufacturing industry j in year t. I specify the outcomes to be log inventory-to-sales ratio and log sales. The regressor of interest, adopter$_{ijt}$, is a time-varying indicator for whether firm i is a JIT adopter in a given year.

Table 1 reports the regression results.[10] Adopters experience a 13% decrease in inventory-to-sales ratios and a 9% increase in sales. The results imply a change of -16% and 4% of one standard deviation in the outcomes, respectively. The regression results allude to the benefits of JIT in the 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 lead adopters to allocate more resources to production.

[9]Figure A1 plots total inventory holdings by type based on my sample. Aggregate and industry-level inventory-to-sales data similarly show that input inventories have declined since the 1980s. With that said, inventory holdings have recently risen, particularly following the last two recessions. I view this as consistent with the notion that firms reassess risks associated with carrying fewer inventories following large shocks.

[10]Appendix A provides additional results relating JIT to higher sales per worker and more precise forecasts devised by managers about their own firms' earnings.

Table 2: JIT Adoption and Firm Volatility

	(1) Std. sales growth	(2) Std. employment growth
Adopter	-0.065***	-0.068***
	(0.009)	(0.019)
Fixed effects	Industry × Year	Industry×Year
Observations	10,710	10,710

Note: The table reports panel regression results from Compustat Annual Fundamentals based on regression (2). The regressor of interest is the firm-year adoption indicator. A lag of the dependent variable is specified as a control. Four-digit SIC codes are specified in the industry-by-year fixed effects. Standard errors are clustered at the firm level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

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

$$y_{ijt} = \gamma \text{adopter}_{ijt} + \beta y_{ijt-1} + \delta_{jt} + \eta_{ijt}, \tag{2}$$

where y_{ijt} now denotes a rolling 5-year standard deviation of sales growth and employment growth for firm i in industry j in year t. Table 2 reports the results. Adopters see a roughly 7% decline in sales and employment growth volatility. This is consistent with the stabilizing role that JIT plays in the model. Due to the lower fixed order costs, firms 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 variation and examining sensitivity to a set of specific events such as macro fluctuations and weather disasters. The regression results accord with the model in that adopters are less insured against unanticipated disruptions, and an economy with more JIT firms is more exposed to unexpected aggregate shocks.

Third, JIT adopters tend to be more cyclical. I quantify this via regressions that interact adoption

Table 3: JIT Adoption and Cyclicality

	Sales growth	Employment growth
GDP growth	1.625***	1.561***
	(0.287)	(0.256)
Adopter × GDP growth	0.467**	0.393**
	(0.199)	(0.188)
Controls	Yes	Yes
Fixed Effect	Industry	Industry
Observations	34,502	34,502

Note: The table reports regression results from Compustat Annual Fundamentals based on regression (3). The independent variable of interest is the interaction between the adopter indicator and GDP growth. Control variables include firm age in the sample, cash-to-assets, sales-per-worker, as well as the adoption indicator. Four-digit SIC fixed effects are specified. Standard errors are clustered at the firm level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% signficance.

with GDP growth:

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

where $\mathbf{X}$ denotes a set of controls. The coefficient γ_3 measures the extent to which JIT firms exhibit more cyclicality. Table 3 reports the regression results. Based on column (1), a 1% increase in GDP growth is associated with a roughly 1.6% increase in sales growth among non-adopters. Adopters experience an additional sales growth increase of 0.47% above this baseline. Turning to column (2), a 1% increase in GDP growth is associated with a 1.6% increase in employment growth among non-adopters, with a further 0.39% increase in employment growth among adopters. Taken together, adopters are around 25-30% more cyclical than non-adopters.

Fourth, JIT adopters are more sensitive to local weather events. I examine this by estimating the following regression:

$$y_{ijt} = \psi_1 \text{adopter}_{ijt} + \psi_2 \text{disaster}_{ijt} + \psi_3 \big[\text{adopter}_{ijt} \times \text{disaster}_{ijt}\big] + \mathbf{X}'_{ijt}\beta + \delta_i + \delta_t + \omega_{ijt}. \tag{4}$$

Table 4: JIT Adoption and Sensitivity to Local Disasters

	Sales	Employment
Disaster	-0.012**	-0.012**
	(0.005)	(0.005)
Adopter × Disaster	-0.029*	-0.030*
	(0.017)	(0.017)
Controls	Yes	Yes
Fixed Effects	Firm, Year	Firm, Year
Observations	43,123	43,123

Note: The table reports weather event regressions from a sample of Compustat firms based on regression (4). The independent variable of interest is the interaction between the adoption indicator and the disaster indicator. Control variables include capital investment rate, sales per worker, ratio of cost of goods to sales, finished goods inventory holdings, adopter indicator, and the disaster indicator. Standard errors are clustered at the firm level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

The "disaster" regressor is an indicator for a severe weather event occurring in a given year. I collect information on county-level weather disasters from NOAA and link these disasters to public firm headquarter zip codes via the aforementioned Barrot and Sauvagnat (2016) links. Table 4 reports the estimation results. On average, a given weather event in my sample predicts an additional 3% decline in JIT firm sales and employment relative to non-JIT firms.[11]

Taken together, the data suggest that JIT adopters benefit from higher profits and smoother outcomes. At the same time, adoption is associated with heightened exposure to aggregate fluctuations and unanticipated shocks as proxied by local weather disasters. My model of heterogeneous firms with an endogenous JIT adoption decision can explain these patterns. The model also allows me to quantitatively assess the impact of JIT amid an unanticipated macro disaster, something that cannot be captured by firm level regressions.

[11] Similar conclusions are drawn when linking firms to their primary suppliers using the Compustat Segment files, and estimating the differential effect that a weather event originating upstream has on the downstream firm based on its JIT status. Appendix A reports these results.

3 A Model of Just-in-Time Production

Having illustrated the essence of the trade-off 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), embedded with JIT and ultimately incorporating large unanticipated disasters rather than traditional business cycle shocks.

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:[12]

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

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:

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

subject to its budget constraint which holds for all t,

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

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

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:

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

Capital evolves according to investment with a time-to-build constraint:

$$K_{t+1} = (1-\delta)K_t + I_t,$$

where $\delta \in (0,1)$ is the depreciation rate of capital. Taking prices as given, the problem of the intermediate goods firm is:

$$\max_{K_{t+1}, L_t} q_t F(K_t, L_t) - w_t L_t - K_{t+1} + (1-\delta)K_t$$

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:

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

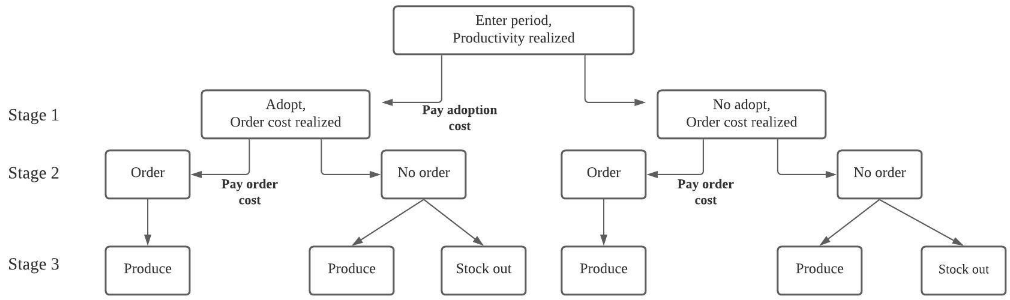
where idiosyncratic productivity evolves as an AR(1) in logs:

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

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,

Figure 1: Decisions of Final Goods Firms



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

and adoption status, a_t. In the first stage, the producers decide 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 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 share information 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. 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, $F(\xi) = U(\underline{\xi}, \overline{\xi})$.[13] 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

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

[13] In Appendix D, I consider an alternate order cost distribution (Khan and Thomas, 2016) which delivers quantitatively similar results.

where the value of placing an order is[14]

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

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

$$\xi^*(z,s,a) = \frac{pqs + V^*(z,s,a) - V^P(z,s,a)}{\phi}. \tag{8}$$

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:

$$V^P(z,\widetilde{s},a) = \max_{s' \in [0,\widetilde{s}]} \pi(z,\widetilde{s},s',a) + \beta \mathbb{E}\big[V^A(z',s',a')\big] \tag{9}$$

where

$$\pi(z,\widetilde{s},s',a) = p\Big[zn(z,\widetilde{s},s',a)^{\theta_n}(\widetilde{s}-s')^{\theta_m} - wn(z,\widetilde{s},s',a) - \frac{c_m}{2}s'^2\Big] \tag{10}$$

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.[15]

[14]The constraint on the order decision allows for only positive orders. In particular, the model abstracts away from inventory liquidation.

[15]The quadratic carrying cost assumed is similar to Luo et al. (2021)

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.[16]

4 Analyzing the Model

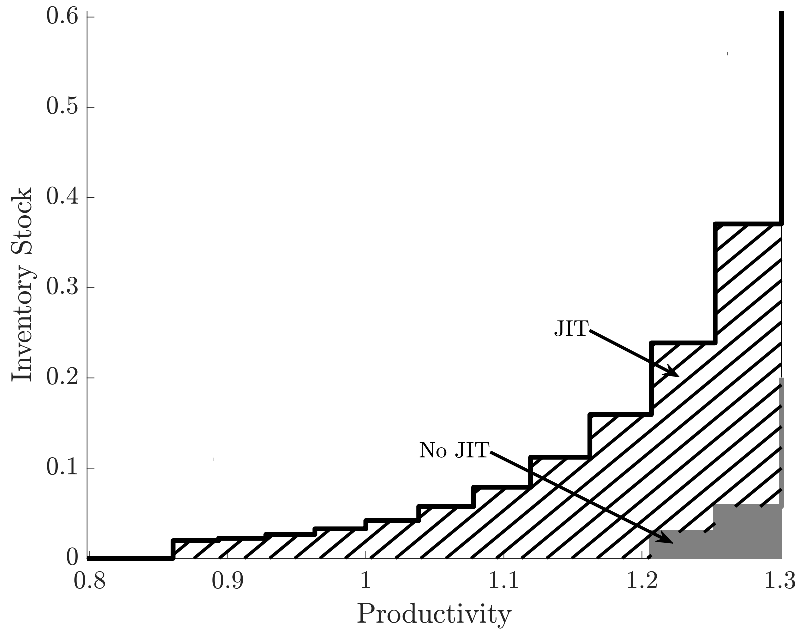
The endogenous adoption decision allows the model to replicate important features of the data, namely, higher profitability and reduced micro volatility among JIT firms. Since implementing JIT comes at a relatively large sunk cost, not all firms optimally choose to adopt JIT. Figure 2 plots the adoption 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 stocking out.

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 inventory stocks and incur fewer carrying costs thereby generating more output.

Figure 3 shows the probability of placing an order as a function of productivity. Consistent with the decision to select into adoption, order probabilities are increasing in productivity and decreasing

[16]In Appendix D, I consider an economy with stockout costs which dissuade producers from allowing $s = 0$, with little impact on the headline results discussed in Section 6.

Figure 2: Adoption Frontiers

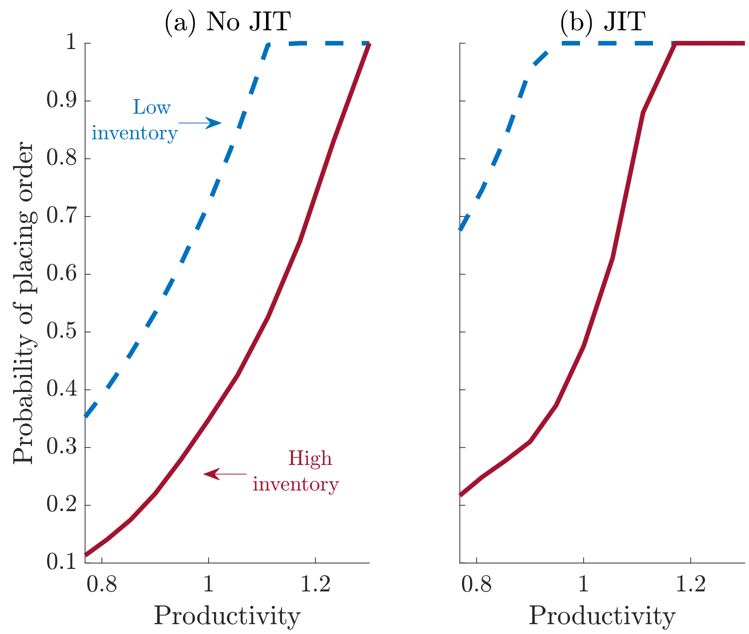


Note: The figure plots the adoption frontier among JIT and non-JIT firms. The solid shaded area plots the region of the state space in which non-JIT firms select into adoption. The striped area along with the shaded area jointly denote the region of the state space in which existing JIT firms choose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

in inventory holdings. Moreover, 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. As a result, adopters in the model place smaller and more frequent orders. This is consistent with the reduction in inventory holdings among adopters.

Figure 4 plots material usage as a function of productivity. Material inputs are increasing in productivity and inventory holdings. Firms with very low inventory stocks will tend to exhaust their remaining inventories regardless of their level of productivity. As a result, the flat lines in these policies reflect endogenous decisions to fully utilize existing inventory stocks in production. Furthermore, adopters make greater use of materials when producing thereby raising output. Because adopters can restock more flexibly, due to the lower order costs, they exhaust their inventory stocks more often. As a result, production among JIT firms tends to be uninterrupted despite their lower inventory holdings. Both the order threshold and the material input policy reflect a treatment

Figure 3: Order Probabilities



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

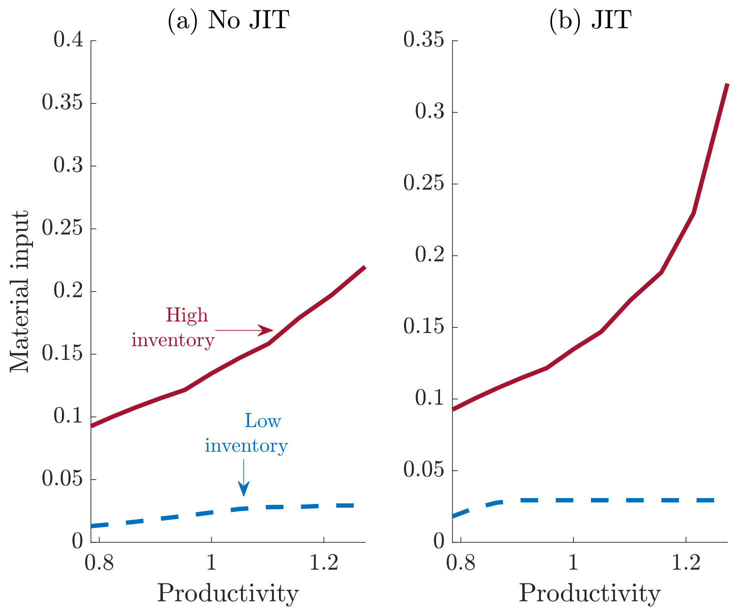
effect that allows firms to produce at lower costs which in turn raises firm sales following adoption.

A comparison of outcomes between economies that differ only in the option to adopt JIT confirms the model-implied benefits to lean production: higher sales and less volatility. Figure 5 visualizes the results from such an exercise. The figure plots a plant's simulated path in both models. The plant in each economy faces the same productivity realizations.

Upon adopting JIT, the establishment retains its status as an adopter through the rest of the simulated path despite lower productivity realizations in the latter periods. This enables the establishment to undertake production despite holding fewer inventories. The cost savings associated with JIT allow the firm to redirect its resources to production rather than order placing or inventory storage. As a result, sales are higher among JIT firms.

Furthermore, upon adopting JIT, the plant's simulated path for orders is smoothed considerably relative to the economy without adoption. This illustrates the insight that JIT mutes the inventory cycle. Because adopters face lower fixed order costs, their target inventory stocks are lower in the

Figure 4: Material Usage



Note: The figure plots material usage policy functions in the production stage as a function of productivity. Panel (a) plots the policy among non-adopters and panel (b) plots the policy for adopters. The solid red line reflects a high inventory establishment in the model while the dashed blue line reflects a low inventory producer.

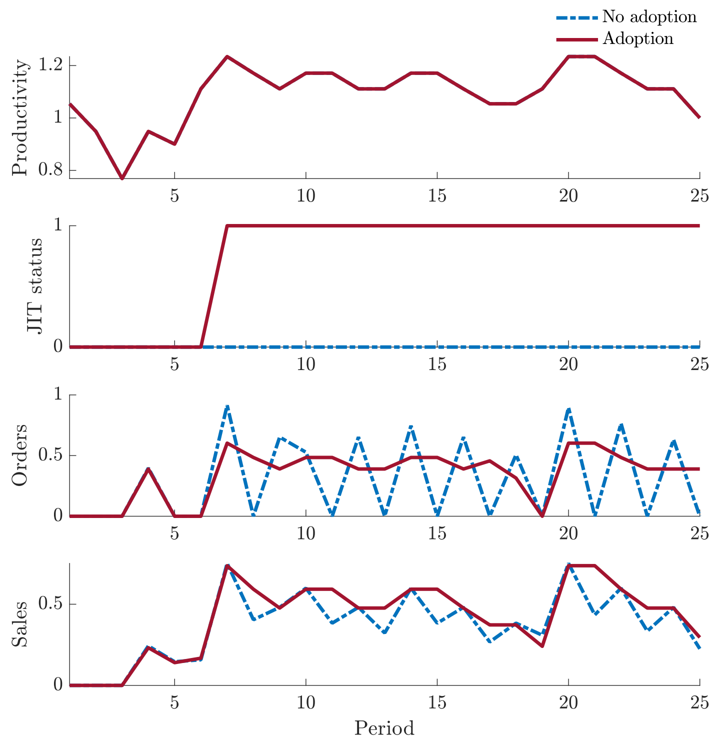
JIT model and the frequency of placing an order increases. The smoother path for orders also smooths firm sales which can explain the lower variance of outcomes among adopters in the data. Lastly, the fourth panel of the figure confirms that JIT producers enjoy, on average, higher sales.

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 adoption frequency, levels of and covariances between inventories and sales, and spikes in inventory holdings. Importantly, the estimated model allows me to quantify benefits to JIT in normal times as well as the vulnerabilities that it engenders to unanticipated macro shocks.

The comprehensive search of firm financials and public statements ensures that the data on JIT adoption do not include false positives. However, information on JIT implementation is constrained

Figure 5: Adoption Mutes the Order Cycle



Note: The figure plots the path of a selected establishment in the unconditional simulation. The top panel plots the (shared) path of idiosyncratic productivity across both models. The second panel plots the plant's JIT adoption status, the third panel plots orders, the fourth plots sales.

to what is reported in these records. To allow for the possibility that JIT is more widespread than the empirical frequency of adoption in my sample, I use the structure of the model in order to infer patterns of adoption. I do so by defining a parameter, $\tau \in (0, 1)$, that governs the share of observed non-adopters from a simulated panel of firms.[17]

There are 16 parameters in the model. I first externally fix seven 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%. Capital depreciation is set to match the average investment rate in the NBER-CES manufacturing data from 1980-2018 (approximately 6.4%). The material share,

[17] 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%
Capital depreciation	δ	0.064	NBER-CES (1980-2018)
Material share	θ_m	0.520	NBER-CES (1980-2018)
Capital share	α	0.420	NBER-CES (1980-2018)
Labor share	θ_n	0.190	Labor share equal to 0.65
Labor disutility	ϕ	2.500	One third of total hours worked
Order cost lower bound (adopters)	$\underline{\xi}_A$	0.000	Lower bound in Khan and Thomas (2007)

Note: The table reports the seven calibrated model parameters.

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 one-third of the time. Finally, I normalize the lower bound of the order cost distribution for JIT producers to zero, consistent with the calibrated lower bound in Khan and Thomas (2007).[18]

5.1 Simulated Method of Moments

The parameter vector to be estimated is $\theta = \left(\rho_z \;\; \sigma_z \;\; \underline{\xi}_{NA} \;\; \overline{\xi}_{NA} \;\; \overline{\xi}_A \;\; c_s \;\; c_f \;\; c_m \;\; \tau\right)'$. These parameters residing in θ govern the exogenous productivity process, the order and adoption costs, the carrying cost, and the share of observed non-JIT firms. 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 11 moments to estimate the nine parameters. My estimator is therefore an overidentified SMM estimator. The first targeted moment is the empirical frequency of adoption.

[18]Rather than fix the lower support of both order cost distributions to zero, I instead include $\underline{\xi}_{NA}$ in the SMM procedure. Since non-JIT firms are expected to face higher average order costs, this approach allows me to more flexibly capture a higher first moment in the non-adopters order cost distribution without necessarily requiring the variance to be higher as well.

Of the remaining 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 inventory-to-sales ratios and log sales (which deliver 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.[19] I specify the asymptotically efficient choice of the weighting matrix which is the inverse of the covariance matrix of the moments.

5.2 Informativeness of Moments

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

Idiosyncratic productivity persistence mostly informs the covariance between inventory-to-sales and log sales. For instance, an increase ρ_z will smooth out firm sales and inventory holdings. Since sales and inventory-to-sales covary negatively, an increase in productivity persistence delivers a more negative covariance between inventory-to-sales and log sales. Moreover, idiosyncratic productivity dispersion mostly affects variances, as an increase in σ_z results in more dispersed outcomes among producers.

The order costs are strongly related to the first and second moments of inventory-to-sales ratios. An increase in the lower bound of the non-adopter order cost distribution leads to a lower level of inventory holdings among non-JIT producers. As the lower bound of the order costs increases, non-adopters face an ever higher average order cost. 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 target inventory stocks are relatively lower.

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 inventory-to-sales ratios for non-adopters. On the other hand, an increase in the upper

[19]The empirical moments are listed in the third column of Table 7.

support of the order cost distribution for adopters leads to higher inventory-to-sales ratios among adopters. While some less productive producers switch out of JIT, the remaining firms raise their target inventory stocks in an effort to lengthen the time between orders. As a result, inventory-to-sales among existing adopters rises.

The adoption costs are largely informed by the covariance between inventory holdings and sales and the variance of sales. An increase in the sunk cost of adoption weakens the covariance between inventory-to-sales and log sales among adopters. Because a higher sunk cost reduces the area representing the adoption frontier for non-JIT producers in Figure 2, only the most productive producers will select into adoption. These highly productive producers, when faced with lower average order costs, substantially reduce their target inventory-to-sales ratios. Furthermore, the variance of inventory holdings also decline leading to a looser covariance between inventory-to-sales and sales. On the other hand, the continuation cost of adoption affects the variance of sales. In particular, a higher continuation cost of adoption reduces likelihood of remaining an adopter conditional on already being one. The marginal producer, which is less productive and more bloated, will therefore switch out of adoption. As a result, the pool of non-adopters faces a wider range of endogenous outcomes since there is now a larger set idiosyncratic productivity realizations that are consistent with being a non-JIT producer. Hence, non-JIT firms see a rise in the variance of log sales.

The convex storage cost affects inventory holdings and spike rates as expected. In particular, higher carrying costs lead firms to lean out across the economy so that inventory-to-sales and spike rates fall among adopters and non-adopters alike. This also implies that the variance of inventory holdings falls across all firms amid a rise in carrying costs. At the same time, the overall variance of log sales rises as some firms can flexibly operate and generate sales in the leaner environment while other firms cannot. Finally, a rise in the the share of observed non-adopters reduces the frequency of adoption, as expected.

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.

Table 6: Estimated Parameters

Description	Parameter	Estimate
Idiosyncratic productivity persistence	ρ_z	0.851
		(0.002)
Idiosyncratic productivity dispersion	σ_z	0.022
		(0.001)
Order cost lower bound (non-adopters)	$\underline{\xi}_{NA}$	0.008
		(0.001)
Order cost upper bound (non-adopters)	$\overline{\xi}_{NA}$	0.451
		(0.006)
Order cost upper bound (adopters)	$\overline{\xi}_{A}$	0.060
		(0.006)
Sunk cost of adoption	c_s	0.201
		(0.002)
Continuation cost of adoption	c_f	0.073
		(0.003)
Carrying cost	c_m	1.037
		(0.009)
Observed share of non-adopters	τ	0.952
		(0.001)

Note: The table reports the estimated parameters with standard errors in parentheses.

(2017). These figures confirm the intuition laid out above.

5.3 Estimation Results

Table 6 reports the estimated parameters, all of which are precisely estimated. The technology parameters, ρ_z and σ_z, are consistent with parameterizations in the literature (Khan and Thomas, 2008; Hennessy and Whited, 2007; Meier, 2020), collectively ranging from 0.68-0.89 and 0.02-0.12 respectively. My estimates imply a more persistent and less dispersed idiosyncratic productivity process than that estimated in Clementi et al. (2015) which is attributable to the fact that my sample consists of public manufacturers who are larger and older than the universe of manufacturers.

The lower bound of the order cost distribution among non-JIT producers is 0.008 while the upper support of the order cost distribution among non-adopters is 0.45. This upper bound is estimated to be an order of magnitude larger than that of adopters, implying that JIT firms place orders that are

Table 7: Model vs. Empirical Moments

Moment	Model	Data
Mean(inventory-sales ratio$\|$adopter)	0.101	0.094
		(0.005)
Mean(inventory-sales ratio$\|$non-adopter)	0.122	0.146
		(0.002)
Std(inventory-sales ratio$\|$adopter)	0.059	0.054
		(0.001)
Corr(inventory-sales ratio, log sales$\|$adopter)	-0.132	-0.098
		(0.001)
Std(log sales$\|$adopter)	0.219	0.206
		(0.005)
Std(inventory-sales ratio$\|$non-adopter)	0.074	0.161
		(0.001)
Corr(inventory-sales ratio, log sales$\|$non-adopter)	-0.307	-0.282
		(0.001)
Std(log sales$\|$non-adopter)	0.267	0.296
		(0.002)
Spike(inventory-sales ratio$\|$adopter)	0.059	0.045
		(0.012)
Spike(inventory-sales ratio$\|$non-adopter)	0.156	0.188
		(0.005)
Frequency of adoption	0.047	0.042
		(0.004)

Note: The table reports model-based and empirical moments with standard errors in parentheses.

about 45% smaller than those of non-JIT firms, indicating a sizable return to adoption for those who can initiate it. Furthermore, the adoption cost estimates suggest a substantial amount of hysteresis in the adoption decision. In particular, firms pay a continuation cost that is slightly more than one third of the original sunk cost. Conditional on being an adopter, the probability of remaining an adopter is 94%. This estimate is similar to 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). The estimated carrying cost is about 20% of the value of inventories, a non-negligible amount that prevents firms from storing too many inventories across periods. Lastly, the estimated share of observed non-adopters implies that the mass of JIT establishments in the model's steady state is about 0.40.

Table 8: Model-Based Regressions

Panel A: Levels		
	Inventory-to-sales	Sales
Data	-0.128 (0.044)	0.090 (0.027)
Model	-0.180 (0.009)	0.060 (0.002)
Panel B: Volatility		
	Sales growth	Employment growth
Data	-0.065 (0.009)	-0.068 (0.019)
Model	-0.046 (0.003)	-0.041 (0.003)

Note: The table reports empirical and model-based panel regressions at the firm level from the estimated and counterfactual models with standard errors in parentheses. Panel A reports regression results as in Table 1. Panel B reports regression results as in Table 2.

Given that I target 11 moments to estimate the nine parameters, the model is overidentified and will not exactly match the empirical moments. With that said, the estimated model fits the data well. Table 7 compares the 11 targeted moments generated by the model with their empirical values. Importantly, the model replicates important features between adopters and non-adopters. Relative to non-JIT firms, adopters hold fewer inventories as a share of their sales. In addition, adopters are broadly characterized by less variable outcomes and a looser association between inventory-to-sales ratios and log sales. Lastly, adopters exhibit fewer spikes in inventory holdings relative to their sales.

5.4 Non-targeted Moments

To further assess the estimated model's ability to match the patterns present in the data, I run empirical regressions based on a panel of simulated firms from both the estimated and counterfactual models. The results are reported in Table 8. The regressions in Panel A are identical to those in Table 1 while the regressions in Panel B are identical to those in Table 2.

Following adoption, the estimated model is able to successfully reproduce reductions in inventory-to-sales ratios. The OLS coefficient from the estimated model resides within the 95% confidence interval of the empirical point estimate. In addition, the estimated model predicts a quantitatively similar increase in sales among adopters. Moreover, the estimated model predicts reductions in firm volatility of 4-5% among adopters, close to the 6-7% estimated declines in the data.

With precisely estimated parameters delivering a broadly successful fit to the data, I can now exploit this structure as a laboratory for quantitative experiments.

6 Quantifying the Trade-off

I proceed to quantify the trade-off between the long-run gains to JIT and the vulnerability to unanticipated disasters 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 economy following a COVID-19 disaster.

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 estimation model with adoption cost parameters c_s and c_f fixed to be prohibitively large such that no adoption takes place. In Appendix C, I conduct a subsample analysis in which I separately estimate the model for the years 1980-1989 and 1990-2018, defining the former period as the relevant counterfactual. The results from this exercise are qualitatively similar to the analysis in this section.

6.1 Steady State

A comparison between the two models points to sizable gains associated with JIT adoption. Table 9 reports the steady state in the estimated model relative to the counterfactual economy in percent deviations. The prevalence of JIT in the estimated model delivers a 9-10% increase in output and implies that smaller and more frequent orders placed such that order demand rises.

As expected, inventory holdings fall in the estimated model. The reduction in inventories is due to a decrease in target inventory stocks across all producers.[20] Relative to the counterfactual,

[20]Non-JIT producers also reduce their inventory targets due to the rise in the price of orders.

Table 9: Long-Run Aggregates Across Models

Output	Order frequency	Order size	Price of orders
9.64	48.45	-19.25	4.76
Inventory stock	**Firm value**	**Measured TFP**	**Welfare**
-35.80	1.30	1.31	1.43

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

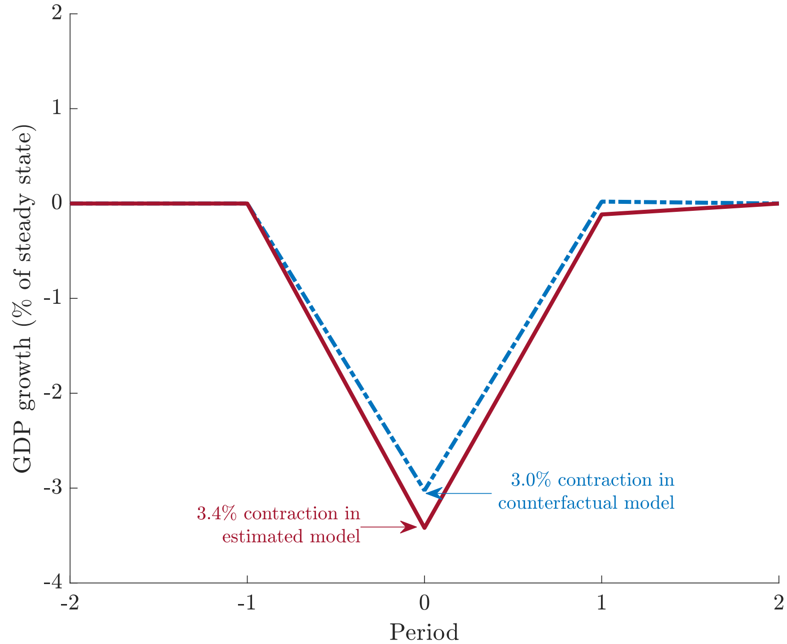
the estimated model delivers a 40% decline in the aggregate inventory-to-sales ratio, close to the observed 35% decline in the ratio of nonfarm inventories to final sales from 1980-2018. In addition, firm value rises by about 1.3% in the estimated model. For reference, the literature measures firm value losses of 2% due to biases in managerial beliefs (Barrero, 2020) and 3% due to CEO turnover frictions (Taylor, 2010). Welfare in the estimated model is 1.43% higher in consumption equivalent terms, a magnitude which resides between the costs of managerial short-termism (Terry, 2017) and static gains to trade (Costinot and Rodriguez-Clare, 2015).

Order costs are a source of dispersion in the model. Ideally firms would like to hold no material inventories, instead placing orders and fully utilizing them when producing every period. In an effort to minimize the number of times the fixed order costs are incurred, producers hold non-zero inventories. For this reason, the estimated JIT adoption model implies an increase in measured TFP. With more adoption, a greater number of producers operate subject to lower order costs. At the aggregate level, this implies that resources are reallocated to high marginal product producers. In essence, firms place more frequent orders and therefore have the flexibility to better align their material usage with their realized micro productivity realizations. The estimated model implies that JIT adoption raises measured TFP by approximately 1.3%.

6.2 Effects of an Unanticipated Disaster

I next show that despite enjoying higher profits and smoother firm-level outcomes, an economy populated by lean producers is more vulnerable to an unexpected disaster. To do this, I introduce

Figure 6: Deeper Crisis with More Adoption



Note: The figure plots the output response to a productivity shock that matches the 3.40% annual decline in real GDP in 2020.

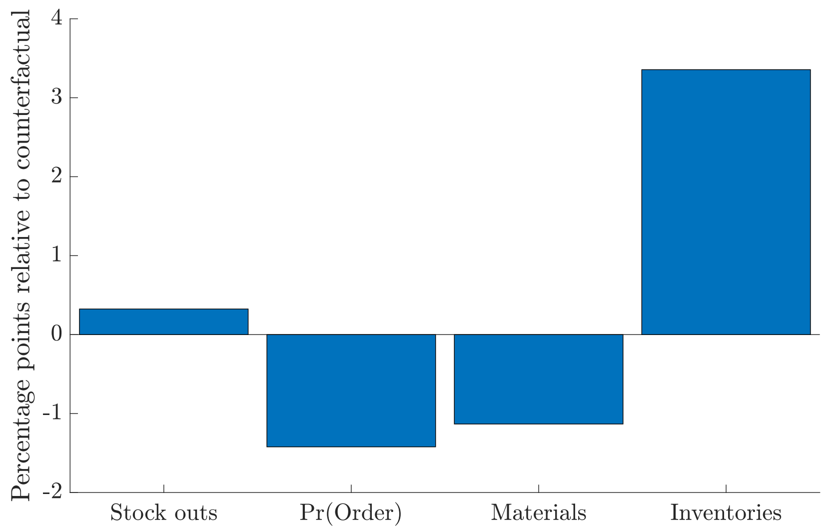
aggregate productivity into the production function for intermediate goods.

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

Whereas in the steady state $A = 1$, in a disaster episode A unexpectedly falls below one.[21] I shock A so as to match the 3.4% drop in real GDP between 2019 and 2020. After this one-time unforeseen shock, I trace the endogenous outcomes in the JIT economy. I then repeat the exercise for the counterfactual economy, keeping the shock to A the same across both economies. Figure 6 displays the output response to this unexpected disaster. In addition, Figure 7 reports the key differences in endogenous responses between the two models amid the disaster.

[21] Consistent with the burgeoning literature studying COVID-19, I model the disaster as an unanticipated event (Arellano et al., 2020; Espino et al., 2020). In Appendix D, I show that my quantitative results are robust to allowing for some anticipation. Appendix D also provides robustness checks including different parameterizations, alternate disaster severities, and the inclusion of stockout costs which serve as a motive for fims to raise their inventory targets.

Figure 7: More Stockouts and Inventory Hoarding



Note: The figure plots the responses of key endogenous variables over the course of the simulated disaster in the estimated economy relative to the counterfactual economy (in percentage points).

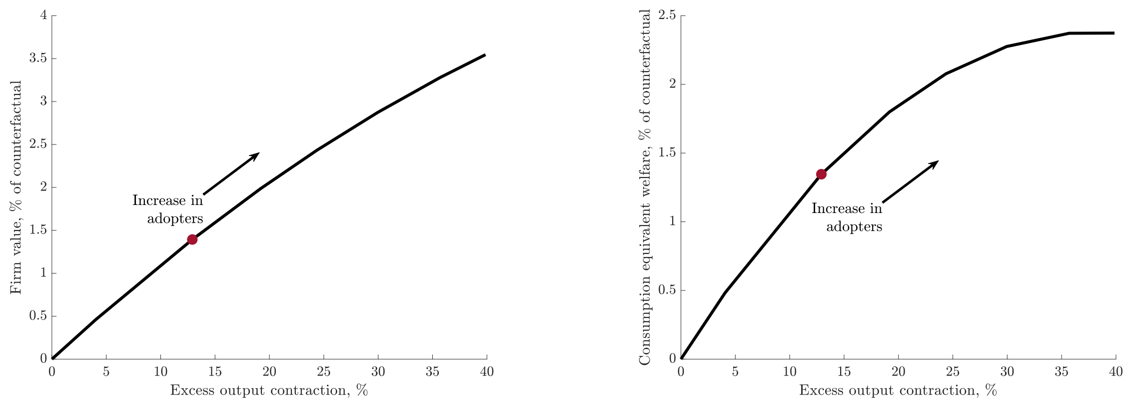
Overall, the JIT economy sees a roughly 0.40 percentage point excess output contraction amid the disaster, amounting to around 13% more than the output lost in the counterfactual model. During an unexpected disaster, the shadow value of inventories rises leading to a spike in stockouts and an overall drop in the likelihood of placing an order. Though both economies experience a decline in inventory holdings, the JIT economy experiences a relative increase in inventories since the leaner firms draw their stocks down more slowly. Due to this hoarding-like behavior, firms in the JIT model make use of fewer material inputs in production, causing sales to contract more sharply.

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 disaster. The excess output loss amounts to approximately \$100 billion, a figure comparable to the funds allocated to state and local governments following the passage of the CARES Act.[22] Lean inventory management therefore plays a meaningful role in determining the vulnerability of the economy to

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

Figure 8: Steady State Gains vs. Macro Vulnerability

(a) Firm Value (b) Welfare



Note: Panels (a) and (b) plot the magnitude of GDP contraction amid a disaster on the horizontal axis. Panel (a) plots the firm value gains in the JIT economy's steady state relative to the no-JIT counterfactual. Panel (b) plots the consumption-equivalent welfare gains. Each point represents a different counterfactual economy, with the estimated economy denoted by the red circle and the no-JIT economy coinciding with the origin. The sunk cost parameters (c_s, c_f) are varied in order to generate the set of counterfactual economies, and the curves are polynomial interpolations these counterfactuals.

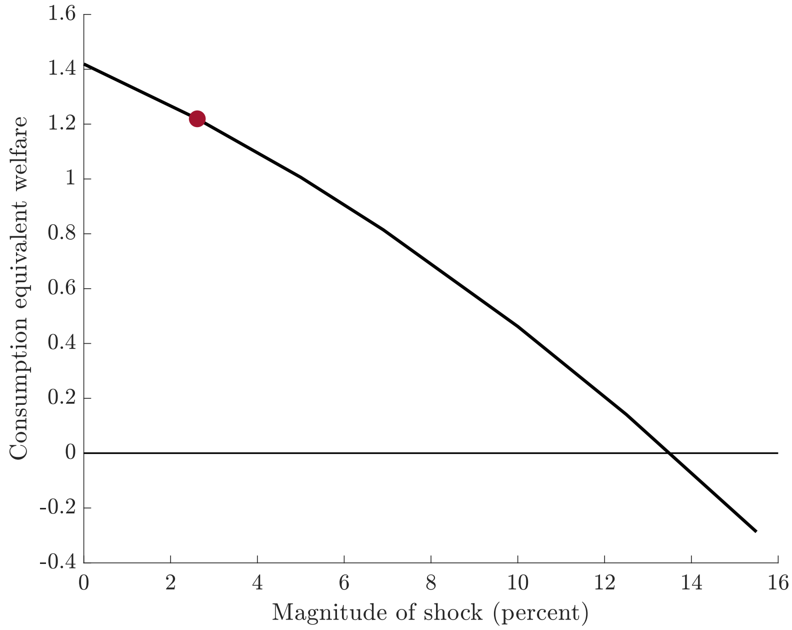
unanticipated shocks. During widespread unanticipated supply disruptions, inventories can serve as a stabilizing force.

6.3 The JIT Trade-off

Having examined the effects of lean inventory management on the economy in normal times as well as amid a COVID-19-magnitude disaster, I next trace out frontiers that illustrate the micro-macro trade-off associated with JIT for a range of counterfactual economies. These frontiers point to an economically important trade-off and imply that inventory management is an important source of aggregate fluctuations amid large unexpected shocks.

Panel (a) of Figure 8 plots the trade-off between firm value and the magnitude of the GDP contraction on impact for several counterfactual economies, each differing in steady state mass of JIT firms. The points on the curve each refer to a specific parameterized economy, traced out by varying the adoption costs, c_s and c_f. The red circle denotes the estimated economy and the origin

Figure 9: Disaster Severity and Welfare



Note: The figure plots the welfare gains in the JIT economy relative to the counterfactual against the size of the unexpected shock. The red circle denotes the welfare gains for JIT under the calibrated shock in the previous section.

denotes the no-JIT economy. The panel shows that average firm value rises with more JIT adoption, at the risk of elevated vulnerability to a shock. A 1.3% increase in firm value comes at the cost of an 13% sharper GDP contraction.

Panel (b) of Figure 8 plots a similar trade-off, this time comparing steady state welfare gains with the magnitude of the GDP contraction. The curve again slopes upward, as welfare gains are increasing in adoption while the extent to which the economy is vulnerable to an unanticipated shock also rises. A 1.4% increase in welfare comes at the cost of an 13% sharper GDP contraction. For reference, the same increase in welfare would arise in a model with no JIT and a 10% reduction in economy-wide order costs. The ranges of this frontier imply an economically large trade-off between long-run gains to JIT and macro vulnerability.

6.4 Welfare Implications of JIT

The exercise in the previous section underscores the vulnerabilities associated with JIT amid the realization of unexpected aggregate shocks. I next examine the welfare implications of JIT. In the calibrated exercise above, JIT remains welfare-improving. This implies that a social planner would not want to reduce the prevalence of JIT in spite of the added volatility brought on amid an unanticipated shock.

While alternative shock severities are capable of reversing this result, I find that such disasters must be far more severe than the simulated COVID-19 shock in the previous exercise. Figure 9 plots the welfare gains to JIT across a range of shock sizes. In order for the planner to prefer a no-JIT world, the negative productivity shock to the orders producer must be almost 14%, an order or magnitude higher than the calibrated productivity shock denoted by the red circle. As a result, the estimated model implies that JIT remains welfare-improving, even amid a COVID-19-like shock.[23]

7 Conclusion

At the firm level, it pays to be lean. I provide empirical evidence of the benefits of JIT inventory management among public manufacturers. Upon adopting JIT, firms hold fewer inventories, and observe higher sales and smoother outcomes. JIT firms, however, appear to be more cyclical and susceptible to disaster episodes. In a heterogeneous firms model in which the most productive firms adopt JIT, lean production raises long-run firm value by 1.3% and welfare by 1.4%. 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 roughly 15% more than a counterfactual economy with no JIT. Adoption, therefore, gives rise to an important and previously unquantified 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

[23]Future work studying alternative drivers of JIT such as investor pressure and imperfect competition, or formally modeling JIT in a more general network structure, could reach different welfare conclusions. Whereas the underlying drivers of JIT can matter for welfare, the outcome of JIT, which is leanness, matters for the trade-off.

shocks, should play close attention to both inventories and 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 three sources. First, I make use of annual Compustat data to obtain information on firm-level inventory holdings as well as sales. Second, I gather data on JIT adoption by reviewing firm financials and financial news. Lastly, I collect county-level weather event data from the National Oceanic and Atmospheric Administration and map them to firm headquarter zip codes.

Compustat Data

I make use of Compustat Fundamentals Annual data from 1980-2018. 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 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, total inventories, and sales.

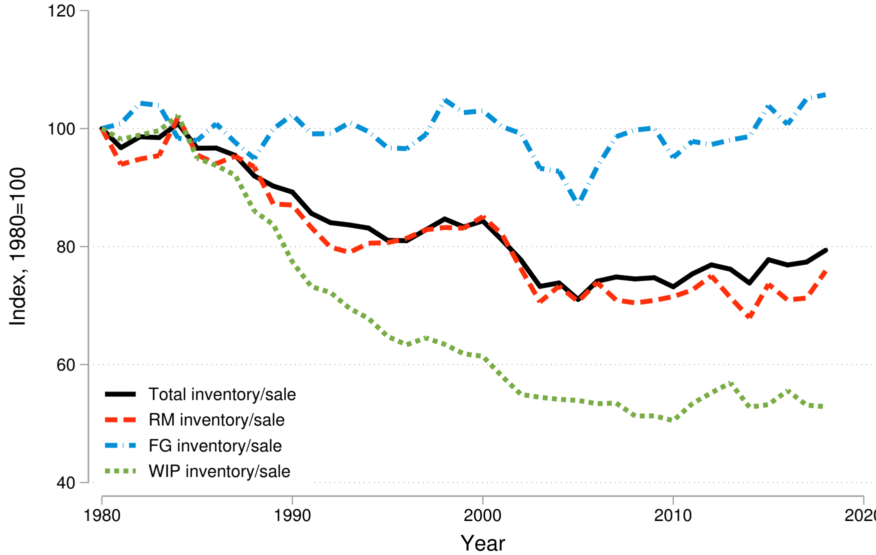
All variables are winsorized at the top and bottom 0.5% of the empirical distribution. Sales growth and employment growth are defined as in Davis et al. (2006)[24]:

$$g_{it} = \frac{x_{i,t} - x_{i,t-1}}{\frac{1}{2}(x_{i,t} + x_{i,t-1})}$$

Lastly because the focus of the paper is on JIT, an input inventory concept, I define the relevant measure of inventories to be the sum of raw material and works in process (`invrm+invwip`). As

[24] These growth rates are the same as log changes up to a second-order approximation.

Figure A1: Compustat Inventory-to-Sales Ratios



Note: The figure plots aggregate inventory-sales ratios from my sample of Compustat firms, by inventory-type. RM = "raw materials," WIP = "works in process," and FG = "finished goods."

indicated by Figure A1 input inventories are the primary contributor to the decline in overall inventory holdings in my sample since 1980, which coincides with the prevalence of JIT.

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 5,017 unique firms. Table A1 reports summary statistics for the variables used.

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. Figure A2 plots the empirical

Table A1: Compustat Summary Statistics

	Mean	Median	Standard Deviation	25%	75%
Employment growth	-0.001	0.000	0.244	-0.083	0.095
Inventory-to-sales	0.142	0.103	0.024	0.063	0.167
Capital investment rate	2.271	1.921	1.910	0.549	3.551
Log sales	4.513	4.483	2.209	2.961	6.038
Sales growth	0.058	0.053	0.302	-0.060	0.168
Log cash-to-assets	-3.014	-2.815	1.555	-4.015	-1.830
Log sales per worker	4.913	4.916	0.779	4.409	5.422
Log employment	-0.400	-0.481	1.924	-1.839	0.956
Age in sample	10.824	9.000	8.527	4.000	15.000

Note: The table reports summary statistics for the relevant variables in estimation in the main text. The sample is constructed from Compustat Fundamentals Annual files for 1980-2018. Sample consists of 5,017 unique firms.

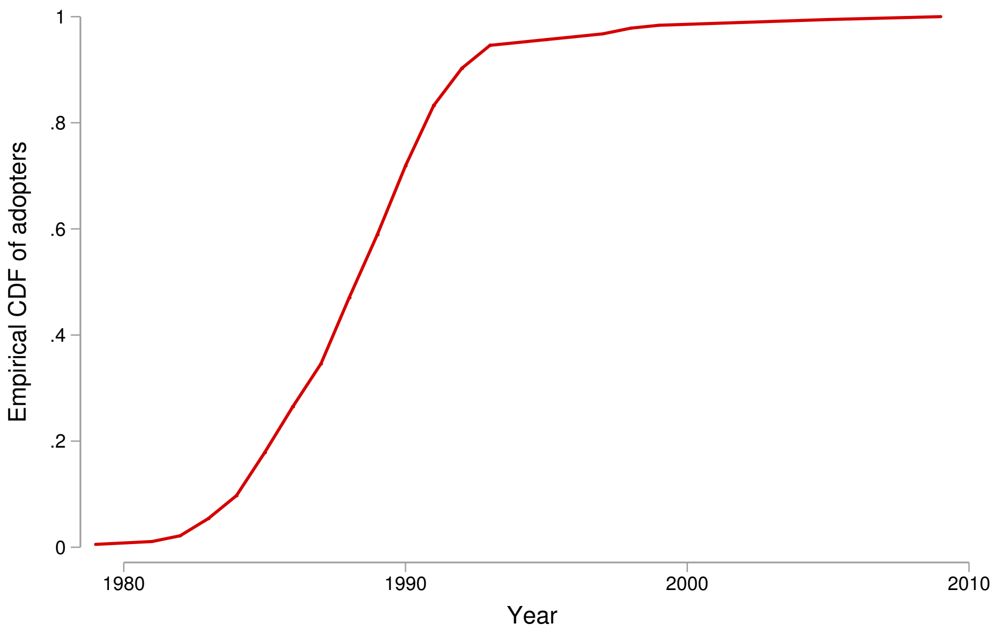
CDF of the adopters in my sample over time.

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.

Figure A2: Adopters by Year



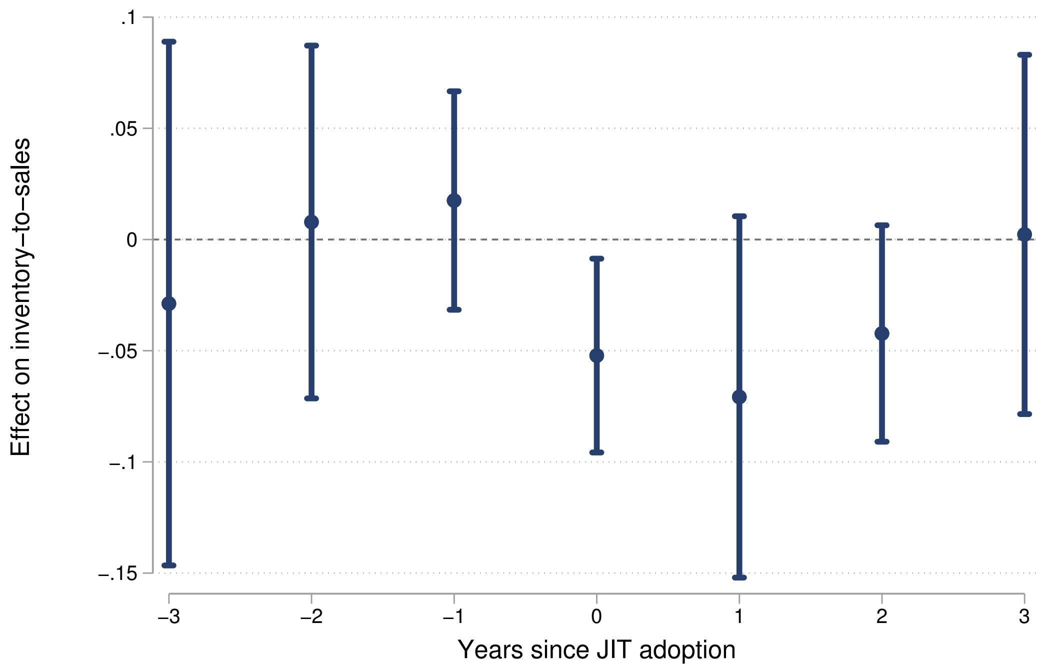
Note: The figure plots the empirical cumulative density function for JIT adoption in the sample.

Whereas in the model I account in part for cross-sectional measurement error, measurement error in the year in which JIT is recorded to have occurred, 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 A3 provides evidence that the recorded years of adoption are accurate. I run the following regression:

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

where the outcomes of interest are the level and first difference in 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 also specified. 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.

Figure A3: 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 alongisde point estimates.

A.2 Additional Results on JIT Adoption and Firm Profitability

Beyond the results reported in Table 1, Table A3 reports additional reduced-form estimates of JIT and firm profitability. Column 1 reports the results from a regression of sales per worker, a basic proxy for productivity, on the JIT adoption indicator as well as fixed effects and other controls. The result indicate that following adoption, JIT firms experience a 5% increase in sales per worker relative to non-JIT firms.

Furthermore, column 2 considers the relationship between JIT adoption and a firm's forecast accuracy. I first merge IBES Guidance data with my JIT adoption data set. The IBES Guidance database provides information on managers' forecasts about their own firm outcomes. I focus on one-year earnings forecasts. After merging these data with my JIT adoption dataset, I obtain a sample of 453 unique manufacturing firms spanning the years 1995-2018. The sample mean of forecast errors is 0.037 with a standard deviation of 1.431. I compute squared forecast errors as the relevant

Table A3: Additional Results on JIT Adoption and Firm Profitability

	(1) Sales per worker	(2) Squared forecast error
Adopter	0.051**	-0.515**
	(0.023)	(0.227)
Fixed effects	Firm, Industry × Year	Industry, Year
Observations	45,357	2,243

Note: The table reports panel regression results from Compustat Annual Fundamentals based on regression (1). The regressor of interest is the firm-year specific adoption indicator. Control variables in the first column include firm age in sample, firm size, and shares outstanding. Standard errors are clustered at the firm level. The standard deviations of the dependent variables are 0.78 and 2.49, respectively. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

measure of forecast accuracy. I then regress the squared errors on the adoption indicator as well as industry and time fixed effects. The results indicate that following adoption, JIT firms observe a -0.515 decline in their squared forecast errors, a roughly 20% standard deviation reduction. Jointly, these facts suggest that JIT firms are more productive and are better able to predict their profitability. The model implies the JIT producers observe an increase in sales per worker, and the improved accuracy lends support to modeling JIT through a reduction in order costs subject to adoption costs.

A.3 Additional Weather Event Regressions

In this section, I further examine the sensitivity of JIT firms to weather events. Rather than considering weather events that directly hit the firm's headquarters, I instead focus on upstream weather events. To do so, I utilize the Compustat Segment files in order to link customer and supplier firms. The Statement of Financial Accounting Standards (SFAS) No. 131 requires public firms to disclose the identity of any customer representing more than 10% of total sales. After linking downstream JIT and non-JIT firms to their major suppliers based on the information disclosed through this regulation, I proceed to link the upstream suppliers to weather events realized in the zip codes where they are headquartered. The series of weather event-to-supplier-to-customer-to JIT status links considerably reduce the sample size to roughly 200 public manufacturers. Nevertheless, I estimate a

Table A4: JIT Adoption and Sensitivity to Local Disasters

	Sales	Employment
Upstream disaster	-0.080**	-0.070*
	(0.034)	(0.036)
Adopter × upstream disaster	-0.085*	-0.071*
	(0.047)	(0.040)
Controls	Yes	Yes
Fixed Effects	Firm, Zip, Year	Firm, Zip, Year
Observations	1,139	1,139

Note: The table reports weather event regressions described in the text. The independent variable of interest is the interaction between the adoption indicator and the average number of upstream weather events experienced by a downstream firms' suppliers. Control variables include customer and supplier age, property damage associated with weather events, customer and supplier finished goods inventories, sales per worker, average order backlog for suppliers, adopter indicator, and the disaster indicator. Standard errors are clustered at the firm level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

negative and significant effect of upstream weather events on downstream firm sales and employment, with greater sensitivity among downstream JIT producers. I run the following regression:

$$y_{ijt} = \psi_1 \text{adopter}_{ijt} + \psi_2 \text{disaster}_{ijt} + \psi_3[\text{adopter}_{ijt} \times \text{disaster}_{ijt}] + \mathbf{X}'_{ijt}\beta + \delta_i + \delta_t + \omega_{ijt},$$

where, as before, the subscripts refer to firm i belonging to industry j in year t. The regression results are reported in Table A4. The upstream disaster variable is the average number of disasters experienced by a downstream firms' major suppliers in a given fiscal year. A unit increase in the average number of disasters experienced by a firm's suppliers predicts a 7-8% decline in firms sales and employment, with a roughly similar excess decline for JIT firms.

A.4 Alternative Measure of JIT Adoption

To explore the robustness of my text-based measure of JIT adoption, I develop an alternate measure of adoption among publicly traded firms by taking a time series approach. The approached is based on the intuition that JIT adopters commit to leaning out. Since they commit to reducing inventory holdings, it stands to reason that upon adopting JIT, a firm would experience a structural break in its mean inventory-to-sales ratio. I implement a cumulative sum of residuals test to detect JIT adoption among the majority of firms in my sample (Ploberger and Kramer, 1992; Brown et al., 1975). To operationalize the structural break test, I narrow my focus to firms with at least five years worth of consecutive observations. In this section, I verify that the structural break approach delivers similar empirical results to the ones reported in Section 2. An appealing aspect of this approach is that it successfully detects JIT adoption among the firms identified through the text-based approach, as well as a wider variety of firms (i.e. manufacturers and retailers.).

CUSUM Approach and Validation

I implement a CUSUM test of OLS residuals for each individual firm time series of inventory-to-sales.[25] In particular, I am interested in detecting structural breaks in the mean level of inventory-to-sales. Let y_t be a firm's inventory-to-sales ratio in year t, this approach requires constructing a test statistic based on the OLS residuals, $\widehat{r}_t = y_t - \widehat{\beta}_0$,

$$B(z) = \frac{\sum_{t=1}^{Tz} \widehat{r}_t}{\widehat{\sigma}\sqrt{T}}$$

where z denotes the break period. When $|B(z)|$ exceeds the relevant critical value, then a break is statistically detected.[26]

In all, this alternate dataset identifies the years in which approximately 560 firms adopted JIT. My final sample consists of an unbalanced panel of 4,005 unique firms spanning the same period as in the main text, and a wider range of industries. Due to the spell length restriction required to

[25] I also implemented a standard CUSUM test and obtained qualitatively similar results.

[26] I select a significance level of 10%.

Table A5: JIT Adoption and Firm Profitability

	(1) Inventory-to-sales	(2) Sales
Adopter	-0.629***	0.164***
	(0.021)	(0.039)
Fixed effects	Firm, Industry × Year	Firm, Industry × Year
Observations	37,266	37,266

Note: The table reports panel regression results from Compustat Annual Fundamentals based on regression (1). The regressor of interest is the firm-year specific adoption indicator. Firm age in the sample is specified as a control variable. Four-digit SIC codes are specified in the industry-by-year fixed effects. Standard errors are clustered at the firm level. The standard deviations of the dependent variables are 0.84 and 2.08, respectively. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

implement the CUSUM test with OLS residuals, the composition of firms across the sample in the main text and the sample used in this section differ. However, of the JIT adopters that reside in both data sets, the structural break approach picks up roughly 72% of the (text-based) JIT adopters.

Empirical Facts

Using these data, I revisit the four facts about JIT adopters presented in the main text. First, JIT adoption is associated with both lower inventory holdings and higher sales. Based on Table A5 , adopters experience a much sharper 63% decrease in inventory-to-sales ratios and a 16% increase in sales. The results imply a change of -75% and 8% of one standard deviation in the outcomes, respectively. The magnitudes in the table are larger than those reported in the main text, mainly due to the fact that adopters are defined as firms that experience sufficiently large drops in inventory holdings so as to trigger a rejection of the null hypothesis.

Table A6 once again indicates that JIT adopters experience less micro volatility. Based on these estimates, adopters see a slightly lower 2-3% decrease in measured volatility.

Third, JIT adopters are more cyclical, as shown in Table A7. The table indicates that a 1% increase in GDP growth is associated with a roughly 0.78% increase in sales growth among non-adopters. Adopters experience an additional sales growth increase of 0.18% above this baseline.

Table A6: JIT Adoption and Firm Volatility

	(1) Std. sales growth	(2) Std. employment growth
Adopter	-0.032***	-0.022***
	(0.008)	(0.007)
Fixed effects	Industry × Year	Industry×Year
Observations	14,647	14,647

Note: The table reports panel regression results from Compustat Annual Fundamentals based on regression (2). The regressor of interest is the firm-year adoption indicator. A lag of the dependent variable is specified as a control. Four-digit SIC codes are specified in the industry-by-year fixed effects. Standard errors are double clustered at the firm and year levels. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Similarly, a 1% increase in GDP growth is associated with a 0.77% increase in employment growth, with a 0.16% further increase for adopters.

Finally, Table A8 shows that JIT adopters are more sensitive to local weather events. While slightly lower, the point estimate in the first column implies that a local weather event predicts about a 3% decline in firm sales.

Table A7: JIT Adoption and Cyclicality

	Sales growth	Employment growth
GDP growth	0.781***	0.774***
	(0.165)	(0.124)
Adopter × GDP growth	0.176*	0.155*
	(0.099)	(0.091)
Controls	Yes	Yes
Fixed Effect	Industry	Industry
Observations	30,016	30,016

Note: The table reports regression results from Compustat Annual Fundamentals based on regression (3). The independent variable of interest is the interaction between the adopter indicator and GDP growth. Control variables include firm age in the sample, cash-to-assets, sales-per-worker, as well as the adoption indicator. Four-digit SIC fixed effects are specified. Standard errors are clustered at the firm level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% signficance.

Table A8: JIT Adoption and Sensitivity to Local Disasters

	Sales	Employment
Disaster	0.009	0.009
	(0.006)	(0.006)
Adopter × Disaster	-0.021*	-0.022*
	(0.012)	(0.012)
Controls	Yes	Yes
Fixed Effects	Firm, Year	Firm, Year
Observations	27,779	27,779

Note: The table reports weather event regressions from a sample of Compustat firms based on regression (4). The independent variable of interest is the interaction between the adoption indicator and the disaster indicator. Control variables include capital investment rate, sales per worker, ratio of cost of goods to sales, finished goods inventory holdings, adopter indicator, and the disaster indicator. Standard errors are clustered at the firm level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Appendix B Model

B.1 Order Threshold for Final Goods Firm

The firm's problem delivers a threshold rule for placing an order. 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

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

and

$$\xi^*(z,s,a) = \min\Big(\max\big(\underline{\xi}, \widetilde{\xi}(z,s,a)\big), \overline{\xi}\Big) \tag{12}$$

B.2 Intermediate Goods Firm

In recursive form, the value of the intermediate goods firm is:

$$W(K) = \max_{K',L}\left\{p\Big[qK^{\alpha}L^{1-\alpha} + (1-\delta)K - K' - wL\Big] + \beta W(K')\right\}$$

Due to the Cobb-Douglas production technology assumed, the intermediate goods firm's value can be expressed as a linear function of the aggregate capital stock. Given this, one can solve for q analytically. In particular, the relative price of the intermediate good is:

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

B.3 Equilibrium

An equilibrium is a set of functions,

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

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:

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

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

4. Market for final goods clears:

$$C = \int\int y(z, s^*, s', a, \xi)dF(\xi^*)d\mu(z, s, a) + \int\int y(z, s, s', a, \xi)[1 - dF(\xi^*)]d\mu(z, s, a) - I.$$

5. Market for orders clears:

$$O = \int\int [s^*(z, s, a, \xi) - s]dF(\xi^*)d\mu(z, s, a).$$

6. Market for labor clears:

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

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

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

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

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

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

and the capital stock evolves according to

$$K' = (1 - \delta)K + I.$$

B.4 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. Furthermore, I select $N_s = 200$ grid points for the endogenous inventory holdings state. Finally, the binary adoption state 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. I then compute 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 using the household's optimality condition. I update the price based on this error using bisection.

For the unexpected shock exercise, I implement a shooting algorithm. I first set the duration of the disaster to be a predetermined length T, so that the model returns to steady state at $T + 1$.

Based on this, I solve the final goods firms problem backwards, obtaining a set of time-indexed policy functions. Using these policies, I then 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 orders market clears.

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 headline results based on an alternate counterfactual.

C.1 Simulated Method of Moments

The parameter vector to be estimated is $\theta = \left(\rho_z \;\; \sigma_z \;\; \underline{\xi}_{NA} \;\; \overline{\xi}_{NA} \;\; \overline{\xi}_{A} \;\; c_s \;\; c_f \;\; c_m \;\; \tau\right)'$. Estimating θ requires making a guess θ_0, solving my plant-level model, and simulating a panel of firms from which I compute the different moments. I define a firm to be composed of ten plants and simulate a panel of firms roughly eight times the size of the panel in Compustat. A firm is defined to be an adopter if at least one of the ten plants adopt JIT, consistent with the classification of JIT firms in my sample. I discard the first 25 years of simulated data so as to minimize the impact of initial values. I then 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.

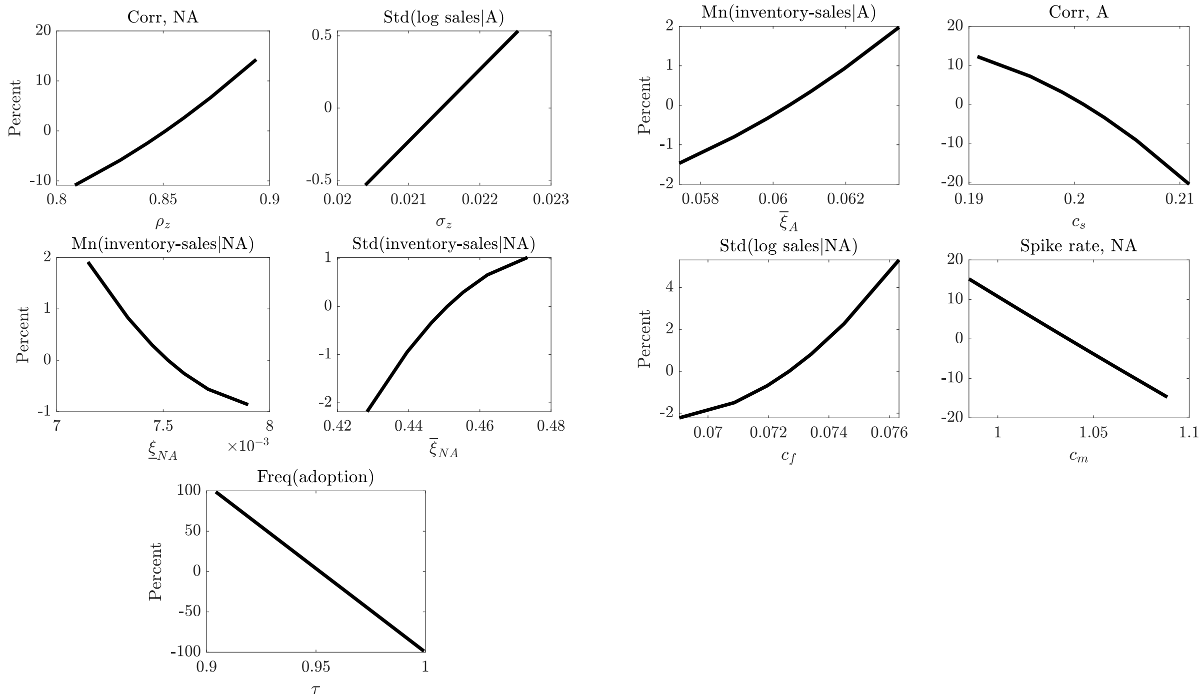
The limiting distribution of the estimated parameter vector $\widehat{\theta}$ is

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

where

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

Figure C1: Monotonic Relationships



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

and S is the ratio of the number of observations in the simulated data to the number of observations in the sample.[27] 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 discontinuities induced by the discretized state space, I select a step size of 1%.

C.2 Identification

The 11 moments jointly determine the nine 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

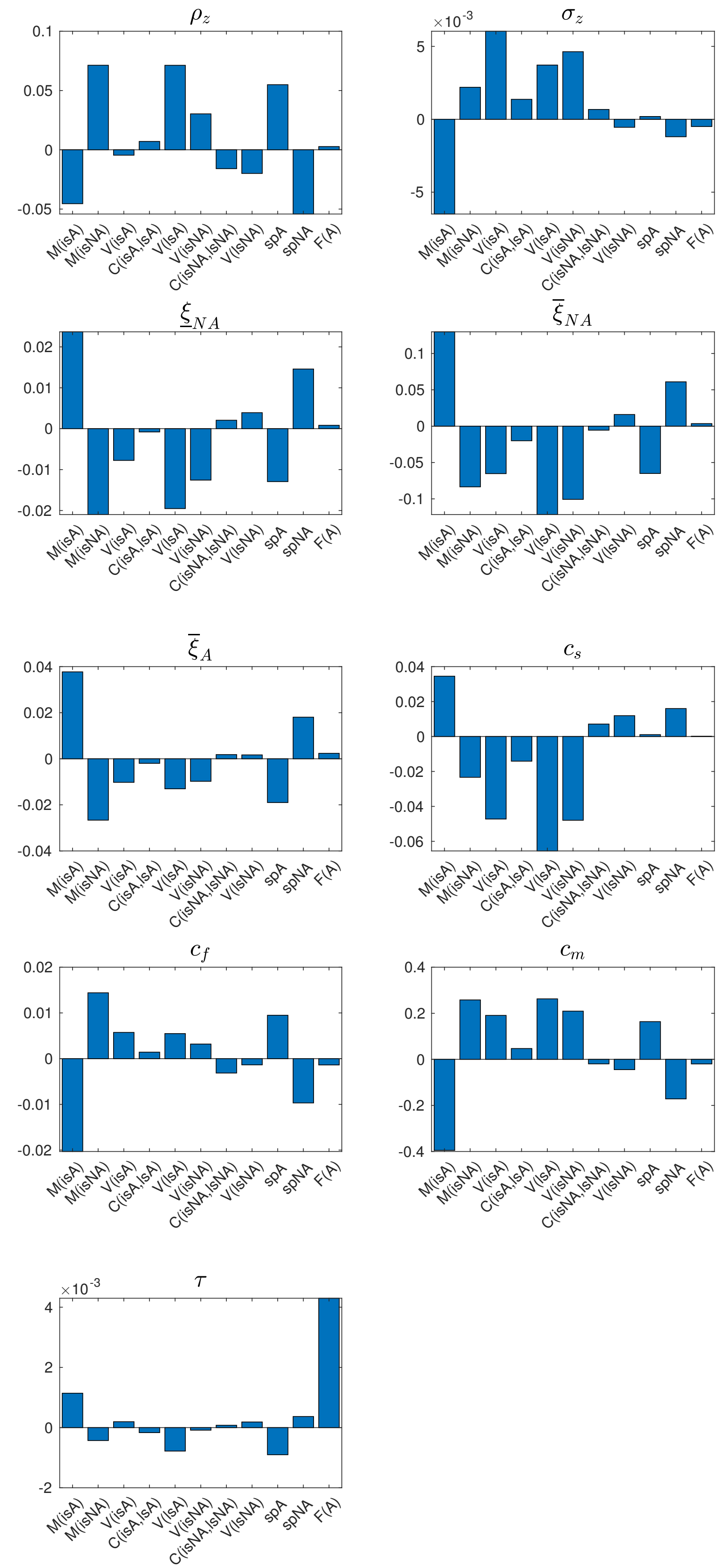
[27] S is set to be approximately 8.

of Andrews et al. (2017). In particular, 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



C.3 Subsample Estimation

In this section, I provide estimates of the model across two sub-periods where the baseline estimates encompass the years 1990-2018 and the counterfactual is estimated from over the years 1980-1989. This alternate counterfactual offers a different point of comparison, a benchmark world in which JIT is not absent but simply less prevalent.

Table C1 reports the estimated parameters from the two models. In order to highlight difference relating directly to the incentives to adopt JIT, I re-estimate only the two adoption cost parameters for the earlier sample. As a result, the counterfactual holds firm level technologies fixed as well as the order costs, carrying cost, and measurement error estimates.

Table C1: Parameterizations for Subsamples

Description	Parameter	1980-1989	1990-2018
Idiosyncratic productivity persistence	ρ_z	0.867	0.867
		-	(0.003)
Idiosyncratic productivity dispersion	σ_z	0.021	0.021
		-	(0.001)
Order cost lower bound (non-adopters)	$\underline{\xi}_{NA}$	0.049	0.049
		-	(0.0004)
Order cost upper bound (non-adopters)	$\overline{\xi}_{NA}$	0.450	0.450
		-	(0.004)
Order cost upper bound (adopters)	$\overline{\xi}_{A}$	0.095	0.095
		-	(0.001)
Sunk cost of adoption	c_s	0.284	0.225
		(0.004)	(0.001)
Continuation cost of adoption	c_f	0.080	0.072
		(0.001)	(0.001)
Carrying cost	c_m	1.239	1.239
		-	(0.006)
Observed share of non-adopters	τ	0.938	0.938
		-	(0.0001)

Note: The table reports the estimated parameters for the subsamples (standard errors in parentheses). Parameters were estimated by targeting the same 11 moments. All nine parameters are estimated for the 1990-2018 sample whereas only c_s and c_f are estimated for the 1980-1989 sample.

The parameters are precisely estimated. The upfront sunk cost of adoption estimated from the

1980's sample is higher at around 26% of the sunk cost estimated in the later sub-sample. The relatively lower sunk cost today implies that it has become easier to initiate JIT production. The estimated per period continuation costs of remaining an adopter are about 11% higher in the earlier sample. While the probability of remaining an adopter conditional on already being one remains at around 95% across both periods, the steady state mass of adopters in the earlier sample is about 35% lower than the later sample.

Table C2 reports the fit of the models. As expected, the baseline 1990-2018 sample provides a more successful fit than the constrained 1980-1989 counterfactual. Table C3 reports the steady state comparisons across models, similar to Table 9. Unsurprisingly, the difference in long-run aggregates is attenuated when the counterfactual features some adoption. For instance, steady state output rises by about 3.4% in the 1990-2018 period relative to 1980-1989. Nonetheless, the results are qualitatively the same: output, measured TFP, and welfare all rise as more firms adopt JIT.

Finally, Figure C3 reproduces the trade-off exercise in Section 6 of the main text. The figure plots two points. One of these points, denoted by the red '+', illustrates the trade-off discussed in the main text. In particular, when estimating the model with the full 1980-2018 sample and comparing it to a no-JIT counterfactual, the firm value gains are at around 1.3% while the excess output contraction amid a one-year disaster is around 13%. The blue 'x' repeats this exercise but for the alternative baseline and alternative counterfactual from the sub-sample analysis. In other words, comparing the steady states of the model estimated from 1990-2018 to the counterfactual encompassing 1980-1989, I find that firm value gains to JIT are slightly higher, at about 1.8%. The slightly higher gains to adoption based on this exercise are attributed to the higher estimated adoption and order costs for non-JIT producers relative to the baseline estimates in the main text. Furthermore, when calibrating an unanticipated disaster to generate a 3.40% contraction the 1990-2018 model, the excess output contraction relative to the contraction in the 1980's model is about 15% close to the baseline estimate.

Table C2: Model vs. Empirical Moments

Moment	1980-1989		1990-2018	
	Model	Data	Model	Data
Mean(inventory-sales ratio|adopter)	0.112	0.111	0.097	0.092
		(0.007)		(0.005)
Mean(inventory-sales ratio|non-adopter)	0.145	0.162	0.116	0.139
		(0.003)		(0.002)
Std(inventory-sales ratio|adopter)	0.053	0.055	0.059	0.054
		(0.001)		(0.001)
Corr(inventory-sales ratio, log sales|adopter)	0.068	-0.213	-0.151	-0.097
		(0.001)		(0.001)
Std(log sales|adopter)	0.235	0.153	0.225	0.209
		(0.004)		(0.005)
Std(inventory-sales ratio|non-adopter)	0.071	0.153	0.073	0.164
		(0.002)		(0.002)
Corr(inventory-sales ratio, log sales|non-adopter)	-0.212	-0.292	-0.340	-0.278
		(0.001)		(0.001)
Std(log sales|non-adopter)	0.310	0.276	0.277	0.305
		(0.003)		(0.003)
Spike(inventory-sales|adopter)	0.035	0.076	0.051	0.042
		(0.028)		(0.013)
Spike(inventory-sales|non-adopter)	0.246	0.239	0.137	0.167
		(0.007)		(0.006)
Frequency of adoption	0.051	0.012	0.061	0.054
		(0.002)		(0.005)

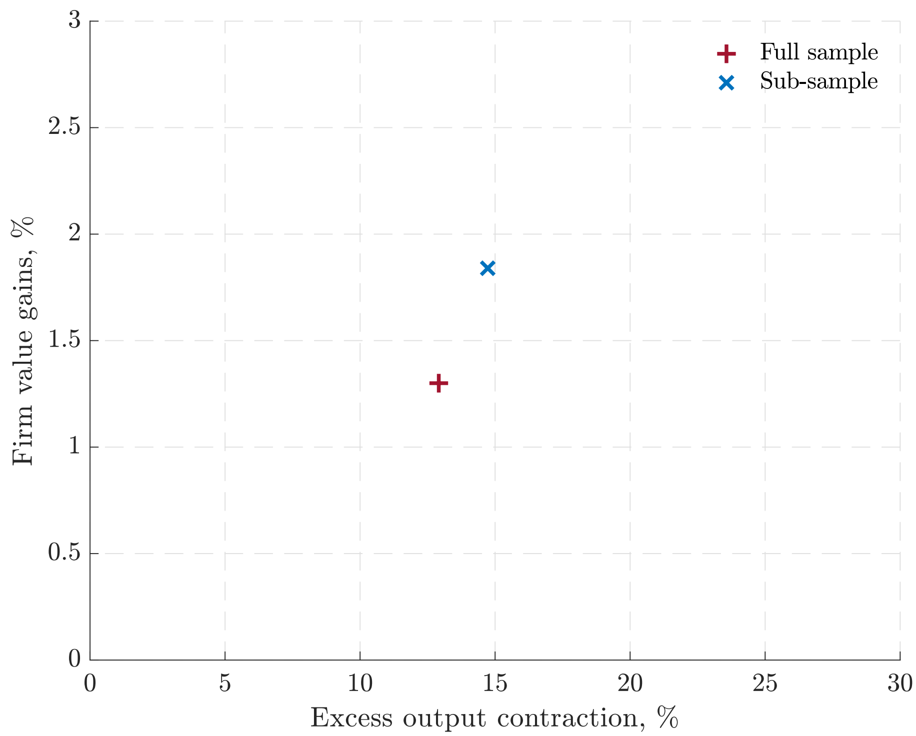
Note: The table reports the model-based moments and the empirical moments for the estimated subperiod models. Standard errors of moments are displayed in parentheses.

Table C3: Long-Run Aggregates Across Models

Output	Order frequency	Order size	Price of orders
3.40	14.67	-7.68	1.78
Inventory stock	Firm value	Measured TFP	Welfare
-17.38	1.84	0.91	1.11

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

Figure C3: Trade-off from Sub-Sample Analysis



Note: The figure plots two points of the trade-off described in the main text. The red '+' illustrates the trade-off between the 1980-2018 model and a no-JIT counterfactual. The blue 'x' plots the trade-off arising from the sub-sample analysis.

Appendix D Robustness

In this section I provide different robustness checks relating to the JIT trade-off presented in the main text. I begin by examining the sensitivity of the trade-off to different parameter values. I then consider a more severe unanticipated shock. Following this exercise, I analyze the role that anticipation plays in the headline results. Next, I study a version of the model that incorporates stockout costs which serve as a motive for firms to carry more inventories in normal times. Lastly, I entertain an alternate order cost distribution.

D.1 Alternate Parameterizations

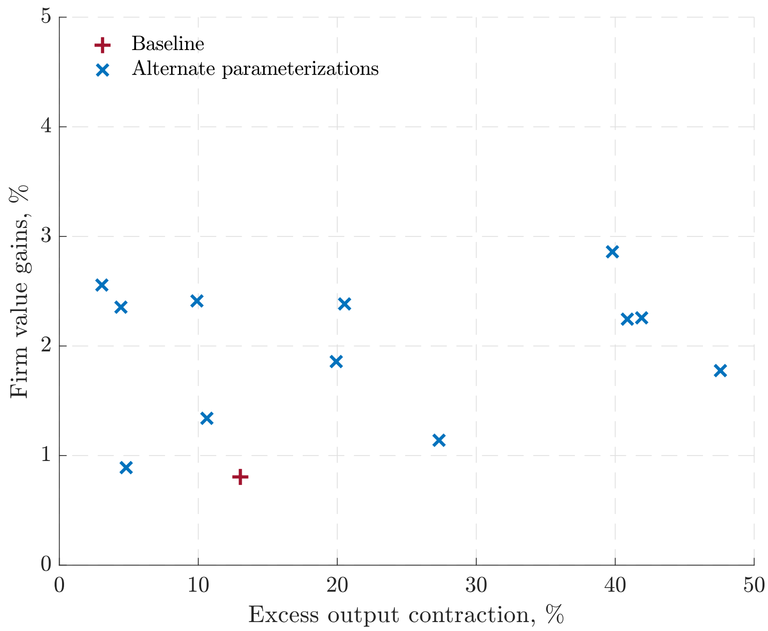
Table D1: Robustness Parameterizations

Description	Parameter	Value	Value
Idiosyncratic productivity persistence	ρ_z	0.950	0.550
Idiosyncratic productivity volatility	σ_z	0.100	0.010
Order cost lower bound (non-adopters)	$\underline{\xi}_{NA}$	0.000	0.050
Order cost upper bound (non-adopters)	$\overline{\xi}_{NA}$	0.600	0.300
Order cost upper bound (adopters)	$\overline{\xi}_A$	0.100	0.050
Carrying cost	c_m	1.300	0.800

Note: The table reports the alternate parameterizations chosen to compute the firm value-aggregate contraction trade-off associated with JIT.

Table D1 reports a number of different parameter specifications. I vary all parameters in different directions with the exception of the adoption costs which trace out the frontier displayed in Figure 8. Figure D1 plots the gap firm value gains against the size of the excess contraction amid a disaster between the JIT and no-JIT economies. The red '+' denotes the headline figure in the main text while the blue 'x' reports the results from the alternate parameterizations. Across all specifications, the firm value gains are robustly coupled with excess output contractions, demonstrating that the micro-macro trade-off consistently remains throughout the range of counterfactual exercises.

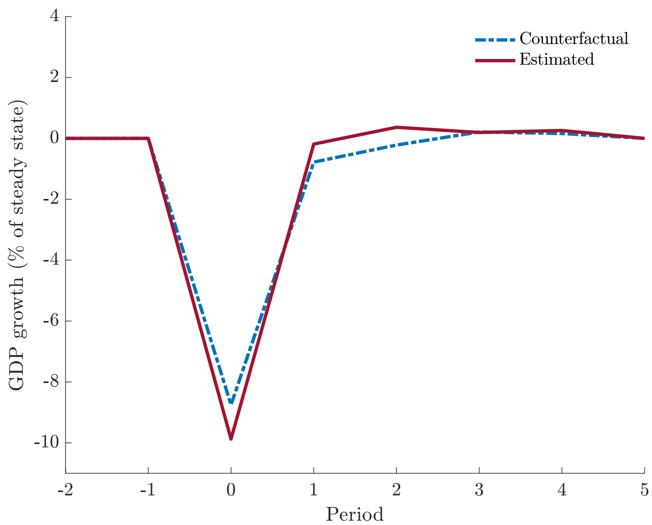
Figure D1: Trade-off Across Alternate Parameterizations



Note: The figure plots the firm value gains against the size of the exceess GDP contraction in the JIT model relative to the no-JIT counterfactual. The red '+' denotes the headline finding in the main text while the blue 'x' reports the trade-offs arising from the different parameterizations detailed in Table D1.

D.2 Disaster Size

Figure D2: Larger Supply Disruption



Note: The figure plots the evolution of output across both models for a disaster that delivers a 10% contraction in the estimated model on impact.

Figure D2 reports the excess output contraction in the estimated economy relative to the counterfactual for a larger disaster, mimicking the contractions observed in the UK and France in 2020. Similar to the baseline findings, the estimated JIT economy contracts more sharply than the counterfactual with no-JIT adoption amid an unexpected drop in A. Over the course of the disaster, the estimated JIT economy contracts by roughly 10% while the counterfactual contracts by 8.7%, implying that the JIT economy experiences a 15% larger contraction.

D.3 Incorporating Partial Anticipation

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

Let λ denote the probability that the large aggregate shock to A 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 disaster as well:

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

The intermediate goods producer similarly faces uncertainty over whether the disaster will come to pass. As a result, the first order condition governing the optimal investment choice becomes:

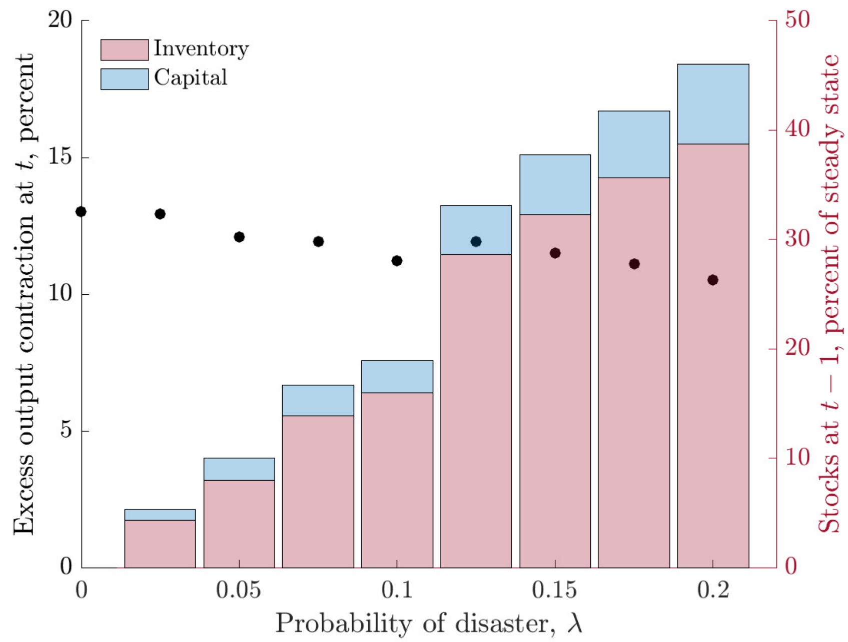
$$p = \beta \left[\lambda \frac{\partial W(A', K')}{\partial K'} + (1-\lambda) \frac{\partial W(1, K_{SS})}{\partial K_{SS}} \right]$$

I evaluate the dynamics amid the disaster shock by numerically 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 push the distribution of firms forward across time utilizing the optimal policies from the backward step. From here, I compute aggregates, check for market clearing, and update the prices until convergence to a specified tolerance.

Figure D3 plots three relevant quantities. On the right axis, I plot the changes in inventory and capital stocks in the period leading up to the shock. As the likelihood that the widespread supply disruption will come to pass 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. At the same time, we observe a rise in capital investment which leads to a higher K' in period $t-1$. The increase in capital investment serves to partially blunt the spike in the price of orders amid the disaster.

On the left axis, I plot the excess output contraction experienced in the estimated economy relative to the counterfactual (in percent). Importantly, despite the added precautionary inventory holdings among firms, and the increase in capital investment, there is still a sizable excess drop in output across the two economies, indicating that the JIT trade-off documented in the main text is robust to the anticipation modeled here. Intuitively, this is due to 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 do not fully appreciate the large negative shock that might come to pass.

Figure D3: JIT Trade-off Robust to Anticipation



Note: The dots, which correspond to the left axis, display the excess output contraction (relative to the no-JIT counterfactual) for different disaster probabilties. On the right axis, the bar plot reports the percent increase in inventory and capital stocks prior to the shock, due to anticipation.

D.4 Incorporating Stockout Costs

The model in the main text assumes that firms have the option to "stock out" and simply forgo production in a given period if they do not receive favorable z and ξ realizations. In this case profits are zero. In reality, however, stockouts can be costly for firms, particularly if one takes the view that firms accumulate customer capital or goodwill. In the event of a stockout, firms might risk losing their customer base, or otherwise developing a reputation for poor management. In this section, I explore the role that costly stockouts play in quantifying the JIT trade-off.

Intuitively, when it is costly for firms to stockout, they will carry more inventories with them and draw existing stocks down more slowly. I model the stockout cost in the firm's production stage decision:

$$V^P(z, \widetilde{s}, a) = \max_{s' \in [0, \widetilde{s}]} \pi(z, \widetilde{s}, s', a) + \beta \mathbb{E}\big[V^A(z', s', a')\big] \tag{13}$$

where

$$\pi(z, \widetilde{s}, s', a) = p\left[zn(z, \widetilde{s}, s', a)^{\theta_n}(\widetilde{s} - s')^{\theta_m} - wn(z, \widetilde{s}, s', a) - \frac{c_m}{2}(s')^2\right] \tag{14}$$

are period profits. A "stock out" occurs when $\widetilde{s} = 0$, so material input usage is zero and the firm produces no output. Rather than earning profits equal to zero amid a stockout, $\pi(z, 0, 0, a) = 0$, I assume that firms must pay a stockout cost, $c_{so} > 0$.[28]

I re-estimate the model with this additional parameter for a total of ten parameters estimated by targeting the same 11 moments. Table D2 reports the estimation results and Table D3 reports the model fit. Compared to the estimated model in the main text, economy-wide inventory stocks in the stockout cost model are roughly 20% larger.

Figure D4 produces a figure similar to Figure C3, where I compare the headline findings in the main text with those implied by a model featuring stock out costs. Since stockout costs raise a firm's motive to carry more inventories, the gains to JIT are slightly less pronounced. With stockout costs, the firm value gains to JIT in normal times amount to roughly 1.2%. At the same

[28] This is essentially a generalization of the baseline model in which $c_{so} = 0$.

time, the unanticipated shock now implies an excess output contraction of about 10% in the JIT economy relative to the counterfactual. All things considered, the stockout cost model delivers a quantitatively similar trade-off to the one documented in the main text.

Table D2: Stockout Cost Model Estimates

Description	Parameter	Estimate
Idiosyncratic productivity persistence	ρ_z	0.813
		(0.001)
Idiosyncratic productivity dispersion	σ_z	0.029
		(0.002)
Order cost lower bound (non-adopters)	$\underline{\xi}_{NA}$	0.006
		(0.001)
Order cost upper bound (non-adopters)	$\overline{\xi}_{NA}$	0.307
		(0.006)
Order cost upper bound (adopters)	$\overline{\xi}_{A}$	0.047
		(0.003)
Sunk cost of adoption	c_s	0.132
		(0.005)
Continuation cost of adoption	c_f	0.070
		(0.001)
Carrying cost	c_m	1.092
		(0.018)
Observed share of non-adopters	τ	0.960
		(0.0001)
Stockout cost	c_{so}	0.621
		(0.008)

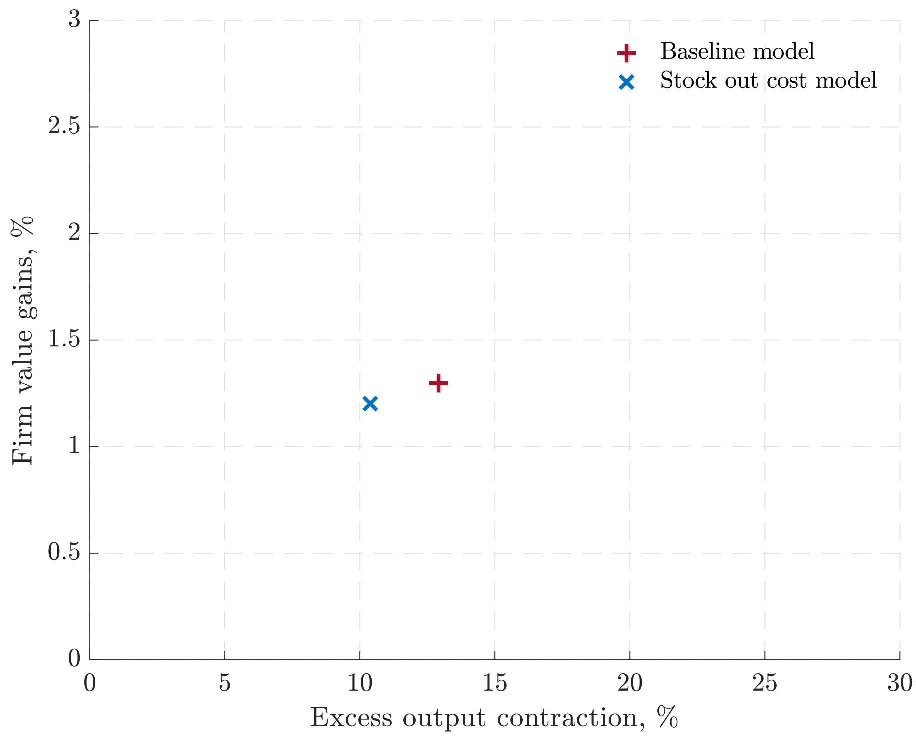
Note: The table reports the parameterization used to define the counterfactual model.

Table D3: Stockout Cost Model Fit

Moment	Model	Data
Mean(inventory-sales ratio|adopter)	0.106	0.094
		(0.005)
Mean(inventory-sales ratio|non-adopter)	0.140	0.146
		(0.002)
Std(inventory-sales ratio|adopter)	0.053	0.054
		(0.010)
Corr(inventory-sales ratio, log sales|adopter)	-0.080	-0.098
		(0.001)
Std(log sales|adopter)	0.213	0.206
		(0.005)
Std(inventory-sales ratio|non-adopter)	0.141	0.161
		(0.001)
Corr(inventory-sales ratio, log sales|non-adopter)	-0.301	-0.282
		(0.001)
Std(log sales|non-adopter)	0.282	0.296
		(0.002)
Spike(inventory-sales ratio|adopter)	0.032	0.045
		(0.012)
Spike(inventory-sales ratio|non-adopter)	0.189	0.188
		(0.005)
Frequency of adoption	0.039	0.042
		(0.004)

Note: The table reports model-based and empirical moments with standard errors in parentheses.

Figure D4: Trade-off with Stockout Costs



Note: The figure plots the JIT trade-off across the baseline model (red '+') and the stockout cost model (blue 'x').

D.5 Alternative Order Cost Distribution

In this section I examine the robustness of the headline findings to the order cost distribution assumed. Rather than assuming that order costs are uniformly distributed, here I assume that they are right skewed as in Khan and Thomas (2016). In particular, let $\xi \sim B(a, b)$ with support $[\underline{\xi}, \overline{\xi}]$. The probability density function of this four-parameter beta distribution is

$$f(x; a, b, \underline{\xi}, \overline{\xi}) = \frac{(x - \underline{\xi})^{a-1}(b - x)^{b-1}}{(\overline{\xi} - \underline{\xi})^{a+b-1}B(a, b)},$$

where $B(a, b)$ is the beta function. I set $a = 5$ and $b = 2$. I then define the location parameters as before. In particular, the lower bound of order costs for adopters is zero, $\underline{\xi}_A = 0$, and the remaining three $\{\underline{\xi}_{NA}, \overline{\xi}_{NA}, \overline{\xi}_A\}$ are estimated from the data.

The parameter estimates are reported in Table D4 and the model fit is reported in Table D5.

Table D6 reports the long run aggregates in the JIT economy relative to the counterfactual. The steady state results with beta distributed order costs are similar to those with uniform order costs. Figure D5 plots the trade-off associated with this model relative to the one reported in the main text. Based on the estimated order cost parameters, the gains to JIT are large, leading to a 1.8% increase in firm value.

Table D4: Beta Cost Distribution Model Estimates

Description	Parameter	Estimate
Idiosyncratic productivity persistence	ρ_z	0.810
		(0.002)
Idiosyncratic productivity dispersion	σ_z	0.023
		(0.0001)
Order cost lower bound (non-adopters)	$\underline{\xi}_{NA}$	0.029
		(0.001)
Order cost upper bound (non-adopters)	$\overline{\xi}_{NA}$	0.285
		(0.001)
Order cost upper bound (adopters)	$\overline{\xi}_{A}$	0.012
		(0.002)
Sunk cost of adoption	c_s	0.213
		(0.003)
Continuation cost of adoption	c_f	0.112
		(0.002)
Carrying cost	c_m	1.308
		(0.005)
Observed share of non-adopters	τ	0.953
		(0.0001)

Note: The table reports parameter estimates with standard errors in parentheses.

Table D5: Beta Cost Distribution Model Fit

Moment	Model	Data
Mean(inventory-sales ratio$\vert$adopter)	0.100	0.094
		(0.005)
Mean(inventory-sales ratio$\vert$non-adopter)	0.123	0.146
		(0.002)
Std(inventory-sales ratio$\vert$adopter)	0.059	0.054
		(0.001)
Corr(inventory-sales ratio, log sales$\vert$adopter)	-0.124	-0.098
		(0.001)
Std(log sales$\vert$adopter)	0.210	0.206
		(0.005)
Std(inventory-sales ratio$\vert$non-adopter)	0.074	0.161
		(0.002)
Corr(inventory-sales ratio, log sales$\vert$non-adopter)	-0.319	-0.282
		(0.001)
Std(log sales$\vert$non-adopter)	0.266	0.296
		(0.002)
Spike(inventory-sales ratio$\vert$adopter)	0.054	0.045
		(0.012)
Spike(inventory-sales ratio$\vert$non-adopter)	0.158	0.188
		(0.005)
Frequency of adoption	0.047	0.042
		(0.004)

Note: The table reports model-based and empirical moments with standard errors in parentheses.

Table D6: Long-Run Aggregates Across Models

Output	Order frequency	Order size	Price of orders
9.30	51.75	-13.01	3.37
Inventory stock	Firm value	Measured TFP	Welfare
-24.37	1.80	0.53	1.46

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

Figure D5: Trade-off with Beta Order Cost Distribution