Spread Too Thin: The Impact of Lean Inventories*

For the most up to date version click here

Julio Ortiz †
Boston University

October 14, 2020

Abstract

Lean production generates a tradeoff between micro stability and macro vulnerability. Examining public just-in-time (JIT) firms, I find that JIT producers experience higher sales growth and less volatility overall. At the same time, JIT producers are more cyclical and sensitive to natural disasters at the macro level. Motivated by these facts, I build and structurally estimate a general equilibrium model in which heterogeneous firms can adopt JIT. The estimated model implies that while JIT producers enjoy a 1% increase in steady state firm value, an unanticipated disaster akin to the COVID-19 shock results in a 1.6 percentage point sharper output contraction relative to a counterfactual economy with less adoption. With more JIT, previously lean businesses stock out more frequently and hoard now highly valuable materials, disrupting their production processes.

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

*I would like to thank Stephen Terry, Adam Guren, and Pascual Restrepo for their many insights, suggestions, and encouragement which greatly shaped this paper. I would also like to thank Ryan Charhour for his valuable feedback and very helpful conversations, as well as the participants of the 2020 BU-BC Green Line Macro Meeting. Lastly, I am grateful to William Wempe and Xiaodan Gao for making their data on JIT adopters available to me.

†Boston University, Department of Economics, 270 Bay State Road, Boston, MA 02215; Phone: 201-230-1960; Email: jlortiz@bu.edu.

1 Introduction

Evolving supply chain practices have led firms to increasingly adopt minimal inventory strategies. While these methods provide scope for eliminating inefficiencies, this paper argues that such strategies render firms more vulnerable to disasters. Specifically, I consider the implications of just-in-time production (JIT), a popular inventory management method that has its roots in postwar Japan. Following the success of Toyota's Kanban system, American auto manufacturers were the first to replicate JIT production. Today, many manufacturers still make use of this inventory management strategy.[1]

The appeal of JIT is attributed to cost reduction. From the perspective that inventories are wasteful, JIT firms commit to reducing stockpiles, instead placing smaller and more frequent orders. As a result, JIT producers incur fewer order and carrying costs. Consistent with empirical evidence that I later present, JIT producers enjoy higher profits and dampened inventory cycles. Amid an unanticipated disaster such as the recent COVID-19 pandemic, however, a rich model of JIT will reveal that an economy with JIT producers experiences a sharper decline in output relative to a counterfactual economy with less JIT. The sharper contraction in the JIT economy is due to the presence of leaner firms. Some of these firms stock out as they are unable to procure materials in the disaster, leading them to fully deplete their inventory holdings. Firms that do not stock out instead hoard materials as inventories become more precious.

I begin my analysis by exploiting data on publicly traded firms that includes JIT adoption status. I then link this to data on macro outcomes as well as local shocks. At the firm level, JIT adoption is associated with a 13% standard deviation increase in sales growth, a meaningful magnitude. In addition, JIT firms tend to hold fewer inventories as a share of their sales and are characterized by less micro volatility. These empirical regularities are consistent with the idea that firms select into adoption and that the JIT process yields firm-level efficiency gains, mechanisms which I will endogenously uncover in my theoretical analysis.

[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.

I then exploit variation external to the firm and document that JIT adopters appear to be more 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 non-JIT firms. In addition, JIT adopters experience sharper drops in sales growth when their suppliers face unexpected weather disasters. My analysis points to higher risk for JIT firms upon the realization of external aggregate shocks, a pattern my theoretical analysis will rationalize.

In light of these empirical facts, I build a dynamic general equilibrium model of JIT production. The model features a rich 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 an order cost. In addition, firms can implement JIT at a fixed cost each period but must pay a relatively larger upfront cost to initiate this practice. Firms adopting JIT benefit from lower average order costs. In a given period, firms must choose their JIT adoption status, whether to place an order, and how much to produce.

I numerically solve and structurally estimate the model via the simulated method of moments (SMM) in order to quantify the JIT tradeoff. Relative to a counterfactual economy with fewer JIT firms, estimated from earlier data in the US before widespread adoption, the estimated model is characterized by a welfare gain of 0.6% and a 0.2% increase in measured TFP in the steady state. Intuitively, JIT adoption leads to an economy-wide reduction in order costs, and an increased frequency of order placement. Since JIT firm are more likely to place an order in a given period, they are better able to align their material input use with their realized productivity. As a result, measured aggregate productivity rises as firms smooth out their inventory cycles, leading to a 9% reduction in firm-level sales volatility.

Whereas individual adopters benefit from JIT in normal times, the existence of leaner firms renders the simulated economy more vulnerable to an unexpected shock. I show this by imposing an unanticipated disaster in both the estimated JIT economy and the counterfactual economy. In particular, the intermediate goods sector faces an unexpected productivity shock. The shock is calibrated to match the drop in real US GDP during the onset of the COVID-19 pandemic. This unforeseen supply chain disruption mimics the nature of the COVID-19 shock, while relating more generally to the evidence on weather disasters considered above.[2]

Relative to the counterfactual economy, the JIT economy experiences a higher frequency of stock outs and a more gradual depletion of inventories. Since JIT firms store fewer materials in their plants, an unexpected spike in order costs makes them more susceptible to stocking out. At the same time, as order costs rise, inventories are suddenly more highly prized, with an increase in the shadow value of inventories within the firm. As a result, firms that do not fully stock out will cut back on material input use in an effort to draw inventories down more slowly. The decision to utilize fewer material inputs in production in the JIT economy implies a sharper drop in output relative to the counterfactual model.

In short, my empirical and theoretical analysis reveals a stark tradeoff between micro stability and macro vulnerability. Firms benefit in normal times from pursuing a lean inventory strategy, however upon the realization of an unanticipated shock, an economy populated by more JIT firms experiences a deeper crisis than one with fewer lean producers.

Inventory investment has long been of interest to economists as a potential source of macroeconomic volatility.[3] Seminal contributions include production smoothing models such as those in Ramey and Vine (2004) and Eichenbaum (1984) as well as (S,s) models as in Scarf (1960) and Caplin (1985). 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. Iacoviello et al. (2011) comes to a similar conclusion albeit through a different model. On the other hand, Wen (2011) builds a stock-out avoidance model and finds that inventories are stabilizing. Moreover Bachmann and Ma (2016) highlights the role that inventories play in a lumpy investment model as an additional means of transferring consumption across time. Inventories can therefore also speak to the macro implications of lumpy investment (Bachmann et al., 2013). I add to the literature on inventories with a

[2]This is also consistent with other work modeling COVID-19 as an unexpected shock (Arellano et al., 2020; Espino et al., 2020).

[3]See for instance Ahmed et al. (2002), McConnell and Perez-Quiros (2000), McCarthy and Zakrajsek (2007), Irvine and Schuh (2005), and McMahon and Wanengkirtyo (2015).

quantitative exercise emphasizing an important tradeoff between micro and macro stability.

In addition, this paper relates to a strand of the management literature that focuses on assessing the gains to just-in-time production. 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. Gao (2018) examines the role of JIT production in corporate cash hoarding. My paper provides a bridge between these findings and the rich literature on inventories in macroeconomics by highlighting how a practice often relegated to management theory, JIT production, matters for the economy as a whole.

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 mapped out networks of customer and supplier firms in order to assess how shocks propagate through the network. For instance, Carvalho et al. (2016) 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 also 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 in the presence of real exchange rate depreciations. My paper adds to the literature on supply chain disruptions, linking it explicitly to an important source of investment at the macro level: inventory accumulation.

Below, Section 2 documents evidence that is consistent with the just-in-time tradeoff. Sections 3 and 4 develop the general equilibrium model of lean production. I estimate the model in Section 5. Section 6 quantifies the just-in-time tradeoff, and Section 7 concludes.

Table 1: JIT Adoption and Profitability

	(1) Inventory-to-sales growth	(2) Sales growth
Adopt	-0.077*** (0.029)	0.034** (0.017)
Fixed effects	Firm, Industry × Year	Firm, Industry × Year
Observations	37,154	37,154

Note: The table reports panel regression results from Compustat Annual Fundamentals of manufacturing firms (NAICS 31-33). The dependent variables are: inventory-to-sales growth and sales growth. The regressor of interest is the firm-year specific adoption indicator. Standard errors are clustered at the firm level. The standard deviations of the dependent variables are 0.30 and 0.26, respectively. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

2 Facts About JIT Adopters

Ultimately my objective is to examine the macro consequences of lean production. I first, however, present some key endogenous facts relating to JIT firms in practice. These facts speak to the JIT tradeoff that I flesh out in detail in the subsequent sections, and the micro data used to document these patterns are also utilized to estimate the model. The following facts also hold at the more aggregated industry level, reported in Appendix A.

I gather firm-level information by making use of Compustat Fundamentals Annual data from 1980-2018. I extend existing datasets on JIT adoption among publicly traded manufacturers (Kinney and Wempe, 2002; Gao, 2018) through an exhaustive textual analysis of news reports and SEC filings.[4] In all, my dataset identifies the years in which approximately 185 Compustat manufacturers adopted JIT. I merge these micro data with US GDP growth. Lastly, I make use of information on local weather events from the National Oceanic and Atmospheric Administration (NOAA) with specific links from Barrot and Sauvagnat (2016). My final sample consists of an unbalanced panel of 5,099 unique manufacturing firms spanning the aforementioned time period.[5]

[4] Specifically, I search news reports and SEC filings for key words such as “JIT,” “just-in-time,” “lean manufacturing,” and “zero inventory.”

[5] Appendix A provides summary statistics of the data.

First, JIT adoption is associated with lower inventory holdings and higher profitability.[6] I show this by estimating the following regression

$$y_{ijt} = \gamma \text{adopt}_{ijt} + \delta_{jt} + \delta_i + \nu_{ijt} \tag{1}$$

where y_{ijt} is an outcome variable for firm i belonging to industry j in year t. The specific outcomes considered are inventory-to-sales ratio growth and sales growth. The regressor of interest, adopt_{ijt}, is an indicator for the year which a firm adopts JIT.

Table 1 reports the regression results. Upon adopting, firms observe a nearly 8 percentage point decrease in the growth rate of inventory-to-sales ratios and a 3 percentage point increase in sales growth. The results imply a change of -25% and 13% of one standard deviation in the outcomes, respectively. The regression results allude to the benefits of JIT in the model. More productive firms select into JIT, incur fewer order costs, and observe decreases in inventory investment and increases in sales growth.

Furthermore, JIT adoption is associated with less micro volatility. Narrowing my focus to eventual adopters in the sample, I run a set of regressions similar to (1) taking second moments as the outcomes of interest. Table 2 reports the results. The estimates imply a roughly 15-20% standard deviation reduction in outcomes following adoption. This is consistent with the stabilizing role that JIT plays in the model. As firms smooth out their inventory cycles, they moderate the variability of other outcomes as well.

I next document facts relating to the other side of the just-in-time tradeoff, 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 aggregate shocks.

Whereas JIT adoption tends to be associated with higher sales growth and lower volatility, it is also characterized by more pronounced cyclicality. I quantify this association via regressions that

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

Table 2: JIT Adoption and Variance of Outcomes

	(1) Inventory-to-sales growth	(2) Employment growth	(3) Sales growth
Adopt	-0.059**	-0.057***	-0.041*
	(0.026)	(0.016)	(0.020)
Fixed effects	Firm, Industry × Year	Firm, Industry × Year	Firm, Industry × Year
Observations	1,749	1,749	1,749

Note: The table reports panel regression results from Compustat Annual Fundamentals of manufacturing firms (NAICS 31-33). The dependent variables are the interquartile range of (1) inventory-to-sales growth, (2) employment growth, and (3) sales growth before and after JIT adoption. The regressor of interest is the firm-year adoption indicator. Firm fixed effects as well as industry by year fixed effects are included. Standard errors are clustered at the firm level. Standard deviation of dependent variables are 0.39, 0.28, and 0.21, respectively. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

interact adoption with GDP growth

$$\text{salegrowth}_{jt} = \gamma_1 \text{adopt}_{ijt} + \gamma_2 \text{GDPgrowth}_t + \gamma_3 \big[\text{adopt}_{ijt} \times \text{GDPgrowth}_t\big] + \mathbf{X}'_{jt}\beta + \delta_j + \varepsilon_{jt} \tag{2}$$

where $\mathbf{X}$ denotes a set of control variables, and firm fixed effects as well as industry fixed effects are specified. The coefficient γ_3 measures the extent to which industries exhibit more cyclicality. Table 3 reports the regression results. At the firm level, adopters see their sales growth increase by an additional 0.8% above the reported baseline. This implies that JIT firms are about 35% more cyclical than non-JIT firms.

Lastly, I turn to weather event data to uncover additional evidence lending support to JIT as a riskier strategy. I estimate the following regression at the firm level

$$\text{salegrowth}_{ijt} = \psi_1 \text{adopt}_{ijt} + \psi_2 \text{disaster}_{ijt} + \psi_3 \big[\text{adopt}_{ijt} \times \text{disaster}_{ijt}\big] + \delta_{jt} + \delta_i + \varepsilon_{ijt} \tag{3}$$

Table 4 reports the estimates. The regression specifies the total number of disasters faced by a firm's suppliers as the relevant disaster variable. A 1% increase in the total number of disasters hitting a firm's suppliers tends to reduce downstream firm sales growth by around 3 percentage points.

Table 3: JIT Adoption and Cyclicality

	Sales growth
GDP growth	2.063***
	(0.082)
Adopter × GDP growth	0.749***
	(0.276)
Fixed Effect	Firm, Industry
Observations	41,571

Note: The table reports regression results from Compustat Annual Fundamentals of manufacturing firms (NAICS 31-33). The dependent variable is sales growth and the independent variable of interest is the interaction between a JIT adoption indicator and GDP growth. Control variables include logs of sales per worker, firm size, cash-to-assets, and inventory stock, as well as the adoption indicator. Standard errors are clustered at the firm level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% signficance.

Adopters experience an additional 6 percentage point drop, an amount about as large as the sample mean of sales growth.

Taken together, the data suggest that JIT adopters see higher profits and smoother firm outcomes. At the same time, adoption is associated with heightened exposure to aggregate fluctuations and unanticipated shocks as proxied by local weather disasters. These empirical results are not interpreted to be causal. Instead, I explicitly model the endogenous adoption decision in the subsequent section. The general equilibrium model predicts endogenous relationships with JIT adoption that are not captured by firm-level regressions and allows for a range of otherwise intractable counterfactual analyses.

3 A Model of Just-in-Time Production

Having illustrated the essence of the tradeoff in the data, I next build the full model which will provide quantitative statements about the implications of JIT. 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 fills orders by using labor and capital. In addition, a continuum of hetero-

Table 4: JIT Adoption and Sensitivity to Local Disasters

	Sales growth
Total upstream disasters	-0.034*
	(0.020)
Adopter $\times$ Total upstream disasters	-0.057***
	(0.017)
Fixed Effects	Firm, Industry $\times$ Year
Observations	1,188

Note: The table reports weather event regressions from a sample of Compustat manufacturing firms (NAICS 31-33). The dependent variable is sales growth and independent variable of interest is the interaction between the adoption indicator and local weather events (total number of upstream disasters). Standard errors are clustered at the firm level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

geneous final goods firms make use of labor and materials to produce using a decreasing returns to scale technology. Firms are heterogeneous in idiosyncratic productivity, inventory stocks, and JIT adoption status. The final good is the numeraire and 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[7]

$$U(C_t, N_t^h) = \log(C_t) + \phi(1 - N_t^h)$$

where $\phi > 0$ denotes the household's labor disutility. The household can work in the intermediate goods sector or the final goods sector and earn wage w_t. The sum of hours worked is denoted by N_t^h. In addition to wage income, the household earns a dividend each period from the firms, D_t, and makes a savings choice, B_{t+1} given interest rate R_{t+1}. The representative household, facing no aggregate uncertainty, maximizes its utility

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

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

subject to its budget constraint which holds for all t,

$$C_t + B_{t+1} \leqslant R_t B_t + w_t N_t^h + D_t$$

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

The representative intermediate goods firm produces orders using capital K_t and labor L_t according to the following constant returns to scale technology

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

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

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

where q_t denotes the price of the intermediate good.

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

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

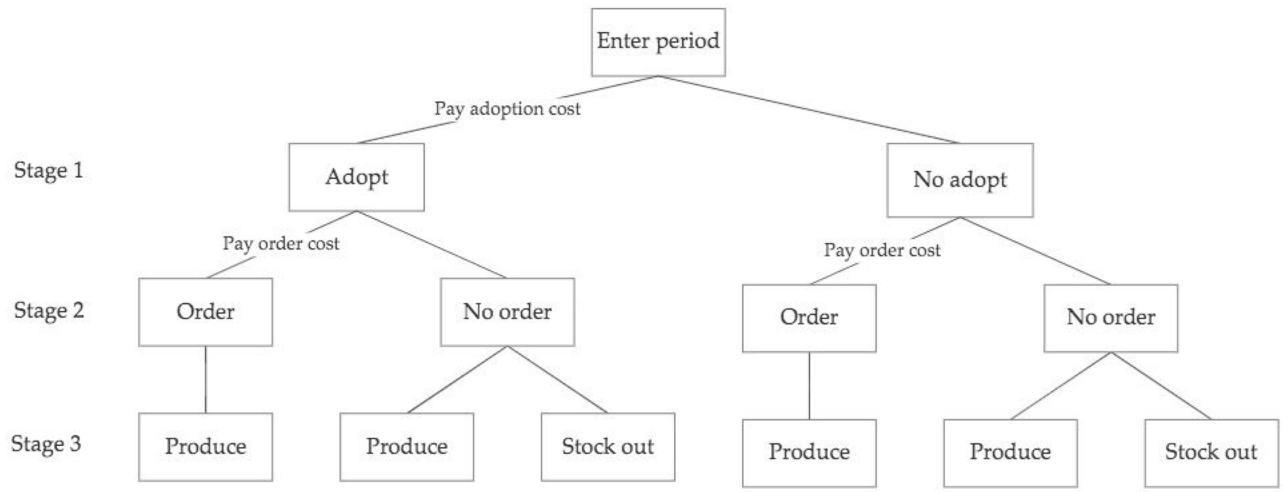
where idiosyncratic productivity evolves as an AR(1) in logs

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

Materials are drawn from the firm's existing inventory stock, s_t, to use in production. A firm's inventory stock is only replenished when orders are placed. Firms face a stochastic order cost drawn from a uniform distribution.

Figure 1 details the final good firms' decision-making timeline. Each period is broken into three stages. A firm enters the period with realized productivity, z_t, inventory stock, s_t, and adoption

Figure 1: Decisions of Final Goods Firms



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

status, a_t. In the first stage, firms assess their state and decide whether or not to adopt JIT. If a firm does not enter the period as a continuing adopter, it must pay c_s in order to adopt. Otherwise, if the firm enters the period as an adopter, it must pay a continuation cost c_f 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 cost, c_s, encompasses all of these one-time costs. The continuation cost, c_f, embodies smaller costs perhaps written into the contract in order for suppliers to participate in timely delivery, costs of training labor on JIT practices and tasks, and greater attention or communication required to share information with suppliers.

In the next stage, firms decide whether or not to place an order, o_t, given the realized order cost $\xi \sim U(0, \overline{\xi})$. JIT producers face a lower order cost distribution, $\overline{\xi}_A < \overline{\xi}_{NA}$. Lastly, following the adoption decision and the order decision, firms 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) and faces adoption costs $\{c_s, c_f\}$, denominated in units of labor. The firm first decides whether to adopt JIT. Note that the adoption status is a binary outcome. The value of adopting is

$$V^A(z, s, a) = \max \left\{ -pwc(a) + \int V(z, s, 1, \xi) dH(\bar{\xi}_A), \int V(z, s, 0, \xi) dH(\bar{\xi}_{NA}) \right\} \tag{4}$$

where

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

The firm's optimal adoption policy, $a'(z, s, a)$, solves this maximization.

Stage 2: Order Decision

Given the firm's order cost draw, ξ, 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 of placing an order is[8]

$$V(z, s, a, \xi) = \max \left\{ -pw\xi + pqs + V^O(z, s, a, \xi), \widetilde{V}(z, s, a) \right\} \tag{5}$$

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

where

$$V^O(z,s,a,\xi) = \max_{s^* \geqslant s} \Big[-pqs^* + \widetilde{V}(z,s^*,a) \Big] \tag{6}$$

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

$$\xi^*(z,s,a) = \frac{pqs + V^O(z,s,a) - \widetilde{V}(z,s,a)}{\phi} \tag{7}$$

Stage 3: Production Decision

Upon making an adoption decision and choosing whether to place an order, the firm then decides how much to produce. Suppose that a firm enters this 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 its value of producing

$$\widetilde{V}(z,\widetilde{s},a) = \max_{s' \in [0,\widetilde{s}]} \pi(z,\widetilde{s},s',a) + \beta \mathbb{E}\big[V^A(z',s',a')\big] \tag{8}$$

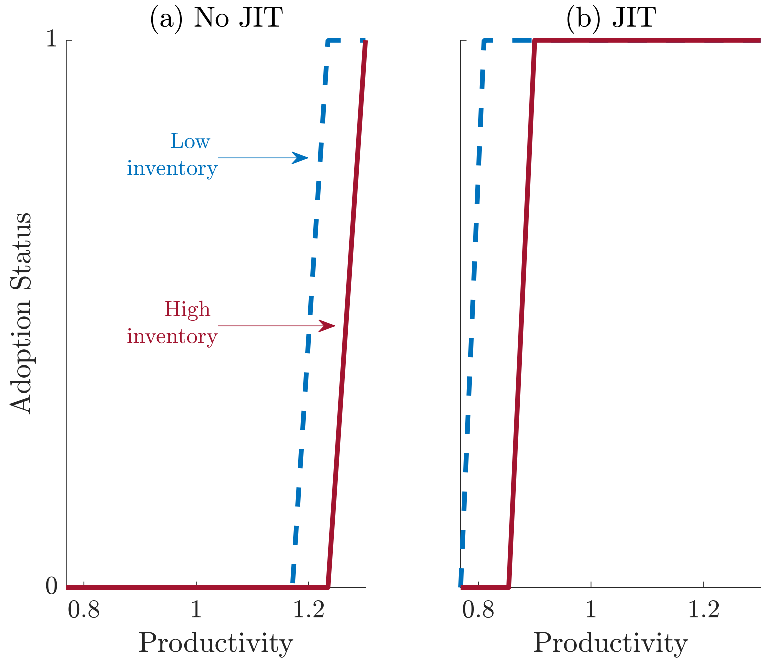
where

$$\pi(z,\widetilde{s},s',a) = p\big[zn(z,\widetilde{s},s',a)^{\theta_n}(\widetilde{s}-s')^{\theta_m} - c_m s' - wn(z,\widetilde{s},s',a)\big] \tag{9}$$

are period profits. The end of period inventory stock is denoted by s', and c_m is the carrying cost of unused input inventory, denominated in units of output.

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 inventories the firm has no material inputs to make use of in the production stage. As a result, it foregoes production in that period, but can restart production in the future conditional on a favorable order cost draw.

Figure 2: Adoption Thresholds



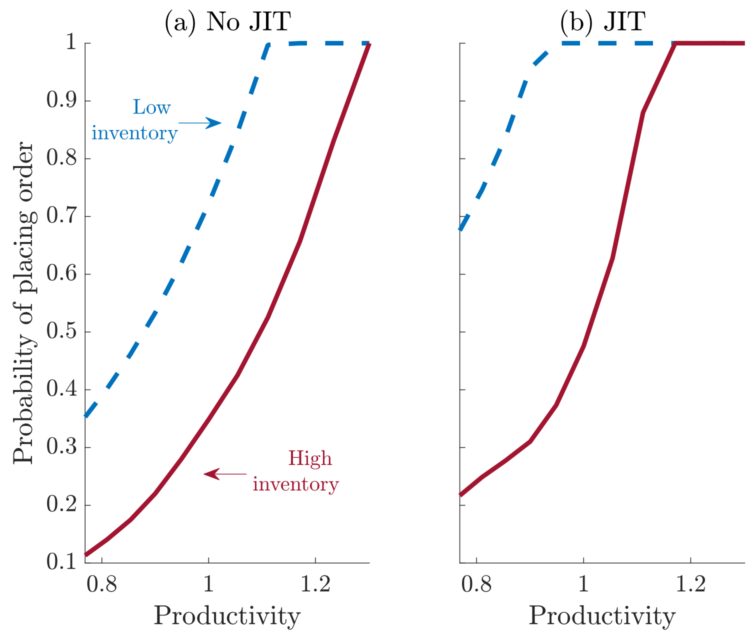
Note: The figure plots the adoption policy in the adoption stage as a function of productivity. Panel (a) plots the threshold among current non-adopters and panel (b) plots the threshold for current adopters. The solid red line reflects a high inventory establishment in the model while the dashed blue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

4 Analyzing the Model

I next examine the role that JIT adoption plays in the model. Since implementing JIT comes at a relatively large sunk cost, not all firms will optimally choose to adopt JIT. Panel (a) of Figure 2 plots the threshold for non-JIT producers as a function of productivity. The panel confirms that there is positive selection into adoption. Moreover, the scope for initiating adoption is decreasing in inventory stocks as the value of adopting is higher among firms that are closer to placing an order.

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. Panel (b) of Figure 2 confirms this intuition. Only the least productive JIT producers will opt to abandon adoption. 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, more productive producers

Figure 3: Order Probabilities



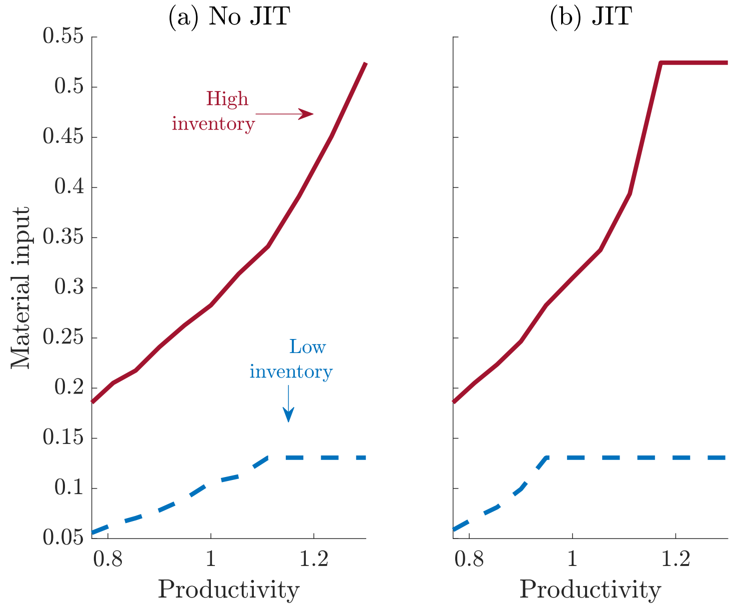
Note: The figure plots the probability of placing an order in the order stage as a function of productivity. Panel (a) plots the threshold among non-adopters and panel (b) plots the threshold for adopters. The solid red line reflects a high inventory establishment in the model while the dashed blue line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

adopt JIT and incur fewer costs thereby observing higher sales growth.

Figure 3 displays order placing probabilities as a function of productivity. These thresholds broadly reflect the adoption thresholds. Consistent with the decision to select into adoption, order probabilities are increasing in productivity and decreasing 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 observed among adopters within an industry, and upon adoption for a given firm.

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. Furthermore, adopters make greater use of materials when producing thereby raising output. The flat lines in these policies reflect

Figure 4: Material Usage



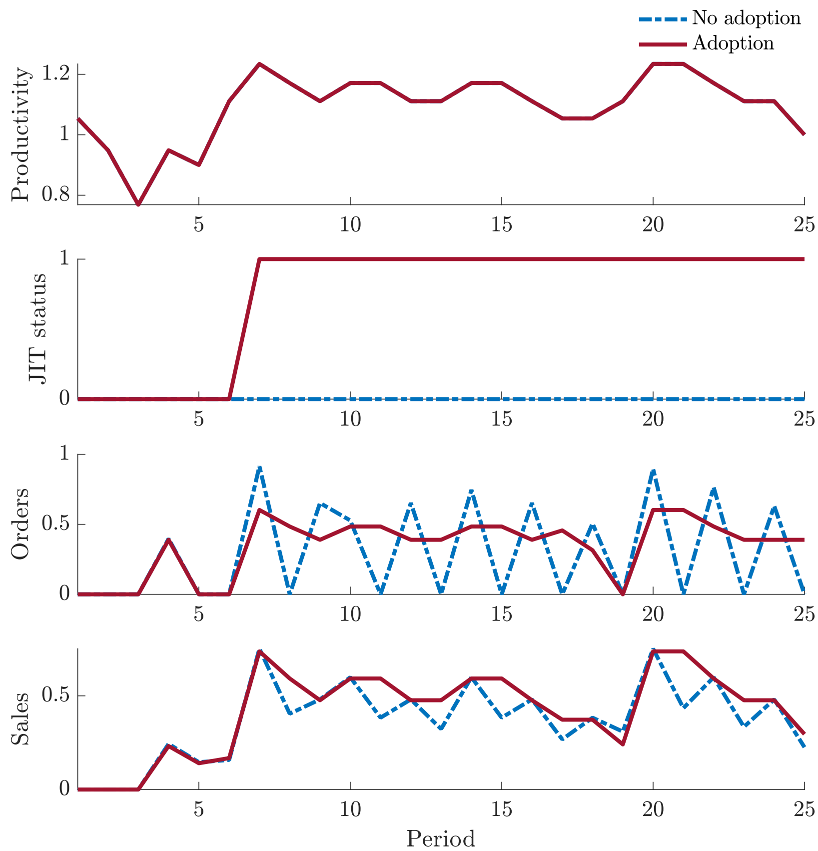
Note: The figure plots material usage policies in the production stage as a function of productivity. Panel (a) plots the policy among non-adopters and panel (b) plots the policy for adopters. The solid red line reflects a high inventory establishment in the model while the dashed blue line reflects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

endogenous decisions to fully utilize existing inventory stocks in production. 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.

Moreover, the model implies that two key benefits to adopting JIT are higher sales and less volatility. I analyze these two results by running an unconditional simulation of the JIT economy and an economy featuring no adoption. Figure 5 plots the simulated path of a random plant 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.

Figure 5: Adoption Mutes the Inventory Cycle



Note: The figure plots the path of a randomly chosen 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 status, the third panel plots orders, and the bottom panel plots sales.

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 JIT model. As a result, the frequency of placing an order increases while the amplitude of the inventory cycle falls. The smoother path for orders also smooths firm sales which can explain the lower variance of outcomes among adopters in the data.

Table 5: External Parameterization

Description	Parameter	Value	Notes
Discount Factor	β	0.962	Real rate equal to 4%
Material share	θ_m	0.520	NBER-CES (1980-2011)
Capital share	α	0.350	NBER-CES (1980-2011)
Labor share	θ_n	0.245	Labor share equal to 0.65
Labor disutility	ϕ	2.400	Work one third of time

Note: The table reports the five calibrated parameters for the model.

5 Structural Estimation

I structurally estimate the model using the micro data on JIT and non-JIT firms. 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 estimation allows me to quantify the just-in-time tradeoff by examining the benefits to JIT in normal times as well as the vulnerabilities that it exposes 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 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.[9]

Of the 13 model parameters, I first externally calibrate five of them based on standard parameterizations in the literature. Table 5 details the annual calibration. The discount factor, β is set to 0.962 which is consistent with a real rate of 4%. The material share, θ_m, and the capital share, α, are set match their counterparts in the NBER-CES database for manufacturers from 1980-2011. 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 about one-third of the time.

[9] 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.

5.1 Simulated Method of Moments

The parameter vector to be estimated is $\theta = \left(\rho_z \;\; \sigma_z \;\; \overline{\xi}_{NA} \;\; \overline{\xi}_A \;\; c_s \;\; c_f \;\; c_m \;\; \tau\right)'$. These parameters residing in θ govern the exogenous productivity process, the stochastic orders costs, the sunk and carrying costs, 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; Gourieroux and Monfort, 1996). 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 eight parameters. My estimator is therefore an overidentified SMM estimator. The first targeted moment is the empirical frequency of adoption. 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, and the frequency of positive inventory-to-sales ratio spikes, defined as instances in which the inventory-to-sales ratio exceeds 0.25.[10] I specify the asymptotically efficient choice of the weighting matrix which is the inverse of the covariance matrix of the moments. The choice of moments is crucial for the identification of the parameters, so I discuss their informativeness in turn.

5.2 Informativeness of Moments

The targeted moments jointly determine the parameters to be estimated. Nonetheless, there are certain moments that are especially informative in pinning down a given parameter. I expand on this by analyzing monotonic relationships between the two.

As expected, productivity persistence informs the covariances while productivity dispersion informs the variances. Moreover, an increase in the order cost distribution for non-adopters raises the inventory-to-sales ratio for JIT firms. Intuitively, higher order costs among non-JIT producers reduces the adoption thresholds in panel (a) of Figure 2 leading more firms to select into adoption.

[10]The empirical moments are listed in the second column of Table 7.

These new adopters are less productive and hold more inventories which raises the overall inventory-to-sales ratio among adopters. On the other hand, an increase in the upper support of the order cost distribution for adopters raises the inventory-to-sales ratio among non-JIT firms. When average fixed order costs rise among adopters, the persistence of adoption falls as less productive and more bloated producers abandon JIT and raise the overall inventory-to-sales ratio among non-adopters.

An increase in the sunk cost of adoption affects the variance of outcomes among adopters while an increase in the continuation cost has implications for the spike rate among non-adopters. An increase in the carrying cost of inventories leads all firms to lean out, thereby reducing spike rates. Lastly, a rise in the the share of observed non-adopters directly affects the frequency of adoption.

Figure C1 in Appendix C outlines these key monotonic relationships between the moments and the parameters. In addition, Figure C2 reports the sensitivity of each of the eight parameters to changes in a given moment, as in Andrews et al. (2017)

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 values in the literature such as Gilchrist et al. (2014) and Winberry (2020). My estimates imply a more persistent and less dispersed idiosyncratic productivity process than that estimated in Clementi et al. (2015) which is likely due to the fact that my sample consists of publicly traded Compustat manufacturers whom are larger and older than the universe of manufacturers.

The upper support of the order cost distribution among non-adopters is estimated to be an order of magnitude larger than that of adopters. These order cost estimates imply that non-JIT firms place orders that are about five times larger than those of JIT firms, indicating a sizable return to adoption for those who can initiate it. Furthermore, the adoption cost estimates suggest a great deal 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 91%. This estimate is similar to estimates of the sunk cost of exporting,

Table 6: Estimated Parameters

Description	Parameter	Estimate
Idiosyncratic productivity persistence	ρ_z	0.878
		(0.059)
Idiosyncratic productivity dispersion	σ_z	0.044
		(0.017)
Order cost distribution (non-adopters)	$\bar{\xi}_{NA}$	0.483
		(0.029)
Order cost distribution (adopters)	$\bar{\xi}_{A}$	0.047
		(0.010)
Sunk cost of adoption	c_s	0.293
		(0.087)
Continuation cost of adoption	c_f	0.110
		(0.012)
Carrying cost	c_m	0.182
		(0.046)
Observed share of non-adopters	τ	0.938
		(0.012)

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

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 15% of the total value of sales, 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 0.15.

Given that I target 11 moments to estimate the eight parameters, the model is overidentified and will not exactly match the empirical moments. With that said, the overidentified SMM procedure 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.

Table 7: Model vs. Empirical Moments

Moment	Model	Data
Mean(inventory-sales ratio$\|$adopter)	0.169	0.146
		(0.005)
Mean(inventory-sales ratio$\|$non-adopter)	0.191	0.194
		(0.002)
Std(inventory-sales ratio$\|$adopter)	0.059	0.042
		(0.0002)
Corr(inventory-sales ratio, log sales$\|$adopter)	-0.185	-0.215
		(0.001)
Std(log sales$\|$adopter)	0.234	0.189
		(0.014)
Std(inventory-sales ratio$\|$non-adopter)	0.071	0.067
		(0.0001)
Corr(inventory-sales ratio, log sales$\|$non-adopter)	-0.374	-0.328
		(0.0004)
Std(log sales$\|$non-adopter)	0.277	0.263
		(0.005)
Spike(inventory-sales ratio$\|$adopter)	0.089	0.071
		(0.015)
Spike(inventory-sales ratio$\|$non-adopter)	0.217	0.223
		(0.005)
Frequency of adoption	0.048	0.050
		(0.005)

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

As JIT has become more common over time, an economy with fewer adopters is a natural benchmark against which to compare the estimated model. I exploit the earlier part of my sample in order to define this counterfactual. Specifically, I hold all parameters of the estimated model fixed except for the adoption costs c_s and c_f. I estimate these two costs based on the earlier period of my sample. The resulting estimates for the adoption costs are $c_s = 0.237$ and $c_f = 0.123$, which implies a lower frequency of adoption. The model reflecting these earlier-period adoption costs will serve as my counterfactual comparison for the estimated economy throughout the discussion below.[11]

[11] Appendix C fully details the subperiod estimation results and counterfactual economy parameterization. Appendix C also describes an alternate counterfactual in which I re-estimate the order costs in addition to the adoption costs with no meaningful changes to the results.

Table 8: Model-Based Regressions

Panel A: Growth rates		
	Inventory-to-sales	Sales
Data	-0.077	0.034
Estimated	-0.196	0.065
Counterfactual	-0.273	0.087
Panel B: Volatility		
	Inventory-to-sales growth	Sales growth
Data	-0.059	-0.041
Estimated	0.067	-0.033
Counterfactual	0.146	-0.018

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

5.4 Nontargeted Moments

To further assess the estimated model's ability to reproduce 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 a predicted reduction in inventory-to-sales growth. Both the estimated and the counterfactual models predict an increase in sales growth upon adoption, with the estimated model delivering a closer match to the empirical coefficient. Moreover, both models miss on the estimated reduction in volatility of inventory-to-sales growth. The estimated model, however, more closely matches the reduction in sales growth volatility that is observed in the data. Overall, the estimated model provides a better fit to the data than the counterfactual. With precisely estimated parameters delivering a broadly successful fit to the data, and a relevant counterfactual defined, I can now exploit this structure as a laboratory for quantitative experiments.

Table 9: Long-Run Aggregates Across Models

Panel A: Levels			
Output	Order frequency	Order size	Price of orders
0.79	7.65	-4.68	0.72
Inventory stock	Firm value	Measured TFP	Welfare
-10.56	0.95	0.23	0.57
Panel B: Volatility			
MP materials	Sales	Labor	
-5.01	-9.22	-8.91	

Note: The table reports steady state values of the estimated model relative to the counterfactual model, in percent deviations. Panel A reports the levels of aggregates. Panel B reports measures of firm volatility from unconditional simulation of 40,000 firms over 50 periods.

6 Quantifying the JIT Tradeoff

Having estimated the model, I proceed to quantify the JIT tradeoff. 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 disaster.

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. The higher prevalence of adoption in the estimated model implies smaller, more frequent orders placed such that order demand rises. Because adopters are able to replenish their inventories more often, there are fewer stock outs in the estimated economy. The lower frequency of stock outs in part contributes to the rise in net sales.

As expected, inventory holdings fall in the estimated model. The reduction in inventories is due to a decrease in target inventory stocks across all firms. Relative to the counterfactual, the estimated model delivers a roughly 11% decline in the aggregate inventory-to-sales ratio, a figure that can account for much of the observed reduction in the macroeconomic time series from 1992-2019. In addition, firm value rises by about 1% 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 0.6% higher in consumption equivalent terms, a magnitude comparable to the costs of business cycles (Krusell et al., 2009) and the costs of managerial short-termism (Terry, 2017).

Furthermore, JIT adoption reduces misallocation. 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 firms. 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 0.2%.

The reduction in misallocation manifests itself in lower firm volatility, consistent with Figure 5. Panel B of Table 9 reports results from an unconditional simulation of firms at the steady state. The variance in marginal product of materials falls in the estimated model relative to the counterfactual model. Furthermore, sales volatility in the estimated model falls by 9% relative to the counterfactual model. For reference, the same reduction in firm sales volatility would be achieved in a model without any JIT and a roughly 45% reduction in order costs.

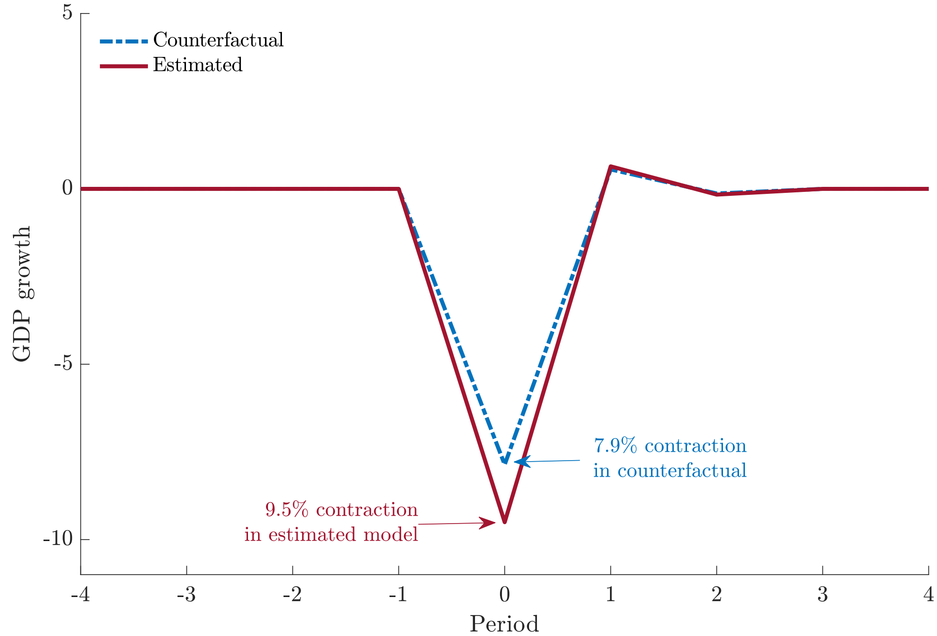
6.2 Effects of an Unanticipated Disaster

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 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. I shock this parameter so as to match the 9.5% drop in year-over-year real GDP in the second quarter of

Figure 6: Deeper Crisis with More Adoption



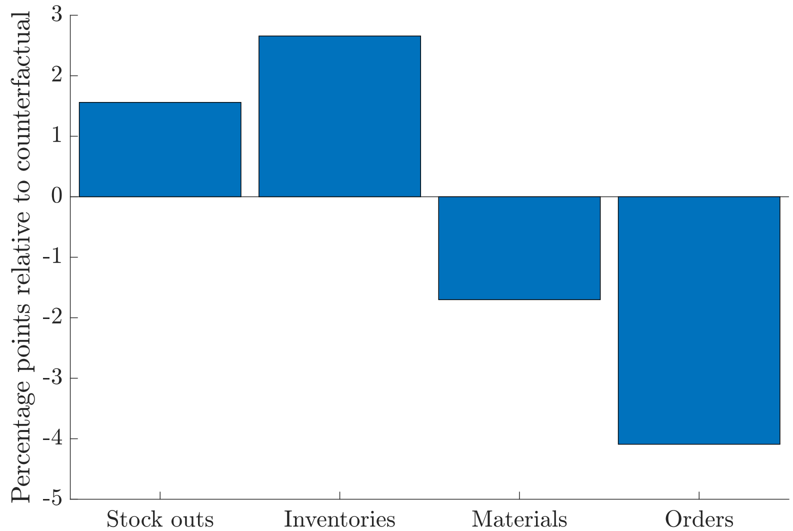
Note: The figure plots the output response to a productivity shock that matches the 9.5% year-over-year decline in real GDP in 2020Q2.

2020. I consider a disaster episode that lasts three years.[12] Figure 6 displays the endogenous output response to this unexpected disaster. In addition, Figure 7 reports the key differences in endogenous responses between the two models over the full disaster path.

Overall, the estimated model sees a 1.6 percentage point sharper output contraction on impact than the counterfactual model. During an unexpected disaster, the shadow value of inventories rises leading firms to reduce order sizes. Since firms in the JIT economy are leaner on average, the JIT economy experiences a 7.5 percentage point sharper spike in stock outs. At the same time, despite a reduction in inventory stocks in both economies, firms in the JIT economy place fewer orders and draw inventories down more slowly. As a result, these firms necessarily make use of fewer material inputs in production and sales contract more sharply in the JIT model. In particular material input

[12]As rare disasters are inherently infrequent, the number of such events is limited in short samples. Here I follow Barro and Ursua (2008) who report a mean duration of 3.5 years from a cross-country panel of disasters. I consider alternate durations in Appendix D with little impact on the qualitative conclusions.

Figure 7: More Stock Outs and Inventory Hoarding



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

use falls 1.8 percentage points more over the course of the disaster in the estimated JIT economy.

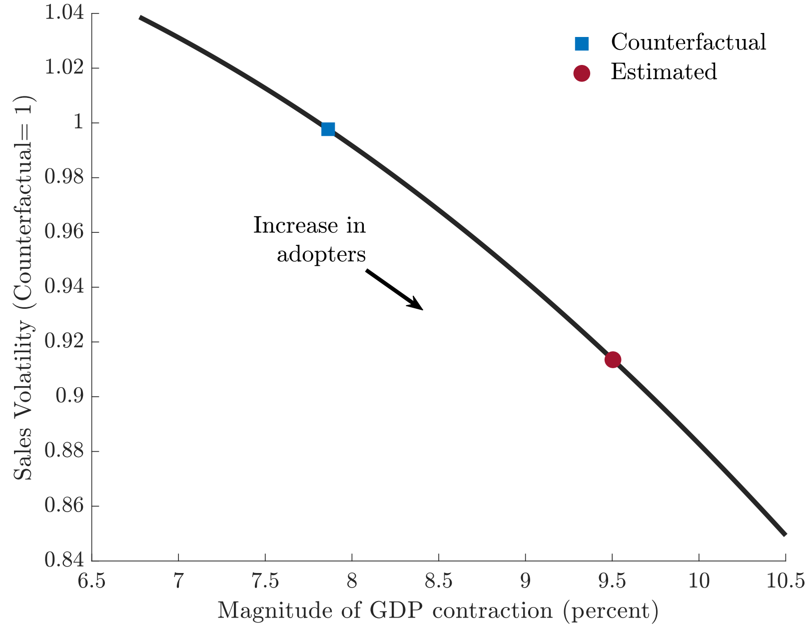
A seemingly minor change to JIT adoption incentives across the two models delivers a substantial difference in the extent to which the economy falls into crisis amid a disaster. The excess output loss amounts to approximately $300 billion, a figure comparable to the funds allocated for direct cash payments to households following the passage of the CARES Act.[13] Lean inventory management therefore plays a meaningful role in determining the vulnerability of the economy to unanticipated shocks.

6.3 The JIT Tradeoff

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 a frontier that illustrates the JIT tradeoff for a range of counterfactual economies. Figure 8 plots the tradeoff between firm sales volatility

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

Figure 8: Sales Volatility vs. Magnitude of Contraction

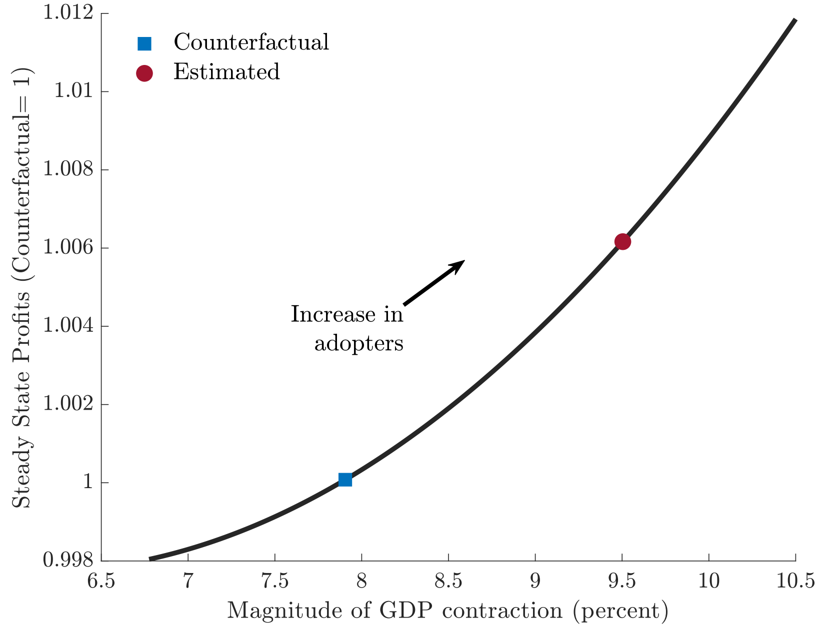


Note: The figure plots an index of the equilibrium firm sales volatility on the vertical axis (relative to the counterfactual economy defined above) and the magnitude of GDP contraction conditional on a disaster. Each point represents a different counterfactual economy, with the estimated economy denoted by the red circle. The sunk cost parameters (c_s, c_f) are varied in order to generate the other counterfactual economies. The curve is a polynomial interpolation of the set of counterfactuals.

and the magnitude of the GDP contraction on impact for several counterfactual economies, each differing in steady state mass of JIT firms. Each point on the curve refers 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 blue square denotes the counterfactual. The figure shows that micro volatility falls with more JIT adoption, at the risk of elevated vulnerability to a shock. A 9% reduction in firm volatility comes at the cost of a 1.6 percentage point sharper GDP contraction.

Figure 9 plots a similar figure, which compares steady state firm profits with the magnitude of the GDP contraction. The curve slopes upward, as steady state firm profits are increasing in adoption while the extent to which the economy is vulnerable to an unanticipated shock also rises. A 0.6% increase in firm profits comes at the cost of a 1.6 percentage point sharper GDP contraction. For reference, the same increase in firm profits would arise in a model with no JIT and a 55%

Figure 9: Profits vs. Magnitude of Contraction



Note: The figure plots an index of the equilibrium firm profits on the vertical axis (relative to the counterfactual economy defined above) and the magnitude of GDP contraction conditional on a disaster. Each point represents a different counterfactual economy, with the estimated economy denoted by the red circle. The sunk cost parameters (c_s, c_f) are varied in order to generate the other counterfactual economies. The curve is a polynomial interpolation of the set of counterfactuals

reduction in economy-wide order costs. The ranges of this frontier imply an economically large tradeoff between measures of micro stability or profitability and macro vulnerability.

7 Conclusion

At the firm level, it pays to be lean. I provide empirical evidence of this among publicly traded manufacturing firms. 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 rich model of JIT production, the most productive firms adopt JIT which increases profitability and micro stability. At the same time, JIT elevates firm vulnerability and risk due to low inventory buffers. Adoption, therefore, gives rise to a highly important macro tradeoff. Economists interested in understanding fluctuations within firms, and the responsiveness of the economy to aggregate shocks, should play close attention to inventories and management practices.

References

Ahmed, Shaghil, Andrew Levin, and Beth Anne Wilson (2002), "Recent U.S. Macroeconomic Stability: Good Policies, Good Practices or Good Luck?"

Alessandria, George and Horag Choi (2007), "Do Sunk Costs of Exporting Matter for Net Export Dynamics?" *The Quarterly Journal of Economics*, 122, 289–336.

Andrews, Isaiah, Matthew Gentzkow, and Jesse M. Shapiro (2017), "Measuring the Sensitivity of Parameter Estimates to Estimation Moments." *The Quarterly Journal of Economics*, 132, 1553–1592.

Arellano, Cristina, Yan Bai, and Gabriel Mihalache (2020), "Deadly Debt Crises: COVID-19 in Emerging Markets." Working Paper.

Bachmann, Rüdiger, Ricardo J. Caballero, and Eduardo M.R.A. Engel (2013), "Aggregate Implications of Lumpy Investment: New Evidence and a DSGE Model." *American Economic Journal: Macroeconomics*, 5, 29–67.

Bachmann, Rüdiger and Lin Ma (2016), "Lumpy Investment, Lumpy Inventories." *Journal of Money, Credit and Banking*, 48, 821–855.

Barrero, Jose Maria (2020), "The Micro and Macro of Managerial Beliefs." Working Paper.

Barro, Robert and Jose Ursua (2008), "Macroeconomic Crises Since 1870." *Brookings Papers on Economic Activity*, 255–335.

Barrot, Jean-Noël and Julien Sauvagnat (2016), "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks." *The Quarterly Journal of Economics*, 131, 1543–1592.

Cachon, Gerard, Taylor Randall, and Glen Schmidt (2007), "In Search of the Bullwhip Effect." *Manufacturing and Service Operations Management*, 4, 457–479.

Caplin, Andrew S. (1985), "The Variability of Aggregate Demand with (S,s) Inventory Policies." *Econometrica*, 53, 1395–1409.

Carvalho, Vasco, Makoto Nirei, Yukiko Saito, and Alrieza Tahbaz-Salehi (2016), "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake." Working Paper.

Clementi, Gianluca, Rui Castro, and Yonsoo Lee (2015), "Cross-Sectoral Variation in the Volatility of Plant-Level Idiosyncratic Shocks." *Journal of Industrial Economics*, 63, 1–29.

Cua, Kristy O., Kathleen E. McKone, and Roger G. Schroeder (2001), "Relationships Between Implementation of TQM, JIT, and TPM, and Manufacturing Performance." *Journal of Operations Management*, 19, 675–694.

Duffie, Darrell and Kenneth J. Singleton (1993), "Simulated Moments Estimation of Markov Models of Asset Prices." *Econometrica*, 61, 929–952.

Eichenbaum, Martin S. (1984), "Rational Expectations and the Smoothing Properties of Inventories of Finished Goods." *Journal of Monetary Economics*, 14, 71–96.

Espino, Emilio, Julian Kozlowski, Fernando M. Martin, and Juan M. Sanchez (2020), "Seigniorage and Sovereign Default: The Response of Emerging Markets to COVID-19." Working Paper.

Fullerton, Rosemary R. and Cheryl S. McWatters (2001), "The Production Performance Benefits from JIT Implementation." *Journal of Operations Management*, 19, 81–96.

Gao, Xiaodan (2018), "Corporate Cash Hoarding: The Role of Just-in-Time Adoption." *Management Science*, 64, 4471–4965.

Gilchrist, Simon, Jae W. Sim, and Egon Zakrajsek (2014), "Uncertainty, Financial Frictions, and Investment Dynamics." NBER Working Paper 20038.

Gourieroux, Christian and Alain Monfort (1996). In *Simulation-Based Econometric Methods*, Oxford University Press.

Iacoviello, Matteo, Fabio Schiantarelli, and Scott Schuh (2011), "Input and Output Inventories in General Equilibrium." *International Economic Review*, 52, 1179–1213.

Irvine, Owen F. and Scott Schuh (2005), "Inventory Investment and Output Volatility." *Interna-*

tional Journal of Production Economics, 93-94, 75–86.
Khan, Aubhik and Julia Thomas (2007), "Inventories and the Business Cycle: An Equilibrium Analysis of (S,s) Policies." *American Economic Review*, 97, 1165–1188.
Kinney, Michael R and William F Wempe (2002), "Evidence on the Extent and Origins of JIT's Profitability Effects." *The Accounting Review*, 77, 203–225.
Krusell, Per, Toshihiko Mukoyama, Aysegul Sahin, and Jr. Anthony A. Smith (2009), "Revisiting the Welfare Effects of Eliminating Business Cycles." *Review of Economic Dynamics*, 12, 393–402.
MacQueen, James B. (1966), "A Modified Dynamic Programming Method for Markovian Decision Problems." *Journal of Mathematical Analysis and Applications*, 14, 38–43.
McCarthy, Jonathan and Egon Zakrajsek (2007), "Inventory Dynamics and Business Cycles: What Has Changed?" *Journal of Money, Credit and Banking*, 39, 591–613.
McConnell, Margaret M. and Gabriel Perez-Quiros (2000), "Output Fluctuations in the United States: What Has Changed Since the Early 1980's?" *American Economic Review*, 90, 1464–1476.
McMahon, Michael and Boromeus Wanengkirtyo (2015), "Beyond Inventory Management: The Bullwhip Effect and the Great Moderation." Working Paper.
Meier, Matthias (2020), "Supply Chain Disruptions, Time to Build and the Business Cycle." Working Paper.
Nakamura, Maso, Sadao Sakakibara, and Roger Schroeder (1998), "Adoption of Just in Time Manufacturing Methods at U.S. and Japanese-Owned Plants: Some Empirical Evidence." *IEEE Transactions on Engineering Management*, 45, 230–240.
Porteus, Evan L. (1971), "Some Bounds for Discounted Sequential Decision Processes." *Management Science*, 18, 7–11.
Ramey, Valerie A. and Daniel J. Vine (2004), "Tracking the Source of the Decline in GDP Volatility: An Analysis of the Automobile Industry." NBER Working Paper 10384.
Rogerson, Richard (1988), "Indivisible Labor, Lotteries and Equilibrium." *Journal of Monetary Economics*, 21, 3–16.
Roumiantsev, Serguuei and Serguei Netessine (2008), "Should Inventory Policy Be Lean or Responsive? Evidence for US Public Companies." Working Paper.
Scarf, Herbert E. (1960), "The Optimality of (S,s) Policies in the Dynamic Inventory Problem." In *Mathematical Methods in the Social Sciences*, 196–202, Stanford University Press, Stanford.
Tauchen, George (1986), "Finite State Markov-Chain Approximations to Univariate and Vector Autoregressions." *Economics Letters*, 20, 177–181.
Taylor, Lucian A. (2010), "Why Are CEOs Rarely Fired? Evidence from Structural Estimation." *Journal of Finance*, 65, 2051–2087.
Terry, Stephen (2017), "The Macro Impact of Short-Termism." Working Paper.
Wen, Yi (2011), "Input and Output Inventory Dynamics." *American Economic Journal: Macroeconomics*, 3, 181–212.
Winberry, Thomas (2020), "Lumpy Investment, Business Cycles, and Stimulus Policy." Working Paper.
Young, Eric R (2010), "Solving the Incomplete Markets Model with Aggregate Uncertainty Using the Krusell-Smith Algorithm and Non-Stochastic Simulations." *Journal of Economic Dynamics and Control*, 34, 36–41.

Appendix A Empirics

This section provides summary statistics of the data used in Section 2 of the main text. The section also includes further details on the JIT adopters data obtained, the weather regression results, and industry-level results.

A.1 Sample Construction

Table A1: Compustat Summary Statistics

	Mean	Median	Standard Deviation	25%	75%
Employment growth	0.005	0.005	0.210	-0.075	0.094
Inventory-to-sales	0.190	0.157	0.244	0.103	0.231
Inventory investment rate	0.035	0.035	0.333	-0.104	0.180
Log sales	4.881	4.769	2.092	3.369	6.292
Sales growth	0.065	0.057	0.261	-0.049	0.167
Log cash-to-assets	-2.533	-2.254	1.546	-3.524	-1.338
Log inventories	2.982	2.885	2.024	1.576	4.348
Log sales per worker	5.093	5.063	0.784	4.545	5.596
Cash-to-assets growth	0.025	0.116	0.868	-0.333	0.360
Log employment	-0.213	-0.330	1.899	-1.635	1.082
Inventory-to-sales growth	-0.018	-0.013	0.305	-0.148	0.120

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 5,099 unique firms.

I make use of Compustat Fundamentals Annual data from 1980-2018. Upon downloading this data, I keep only manufacturing firms (NAICS 31-33). 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. In addition, I keep only firms that exist in the data for at least two years. My final sample consists of 5,099 unique firms. Table A1 reports summary statistics for the variables used.

Table A2: Additional JIT Adopters

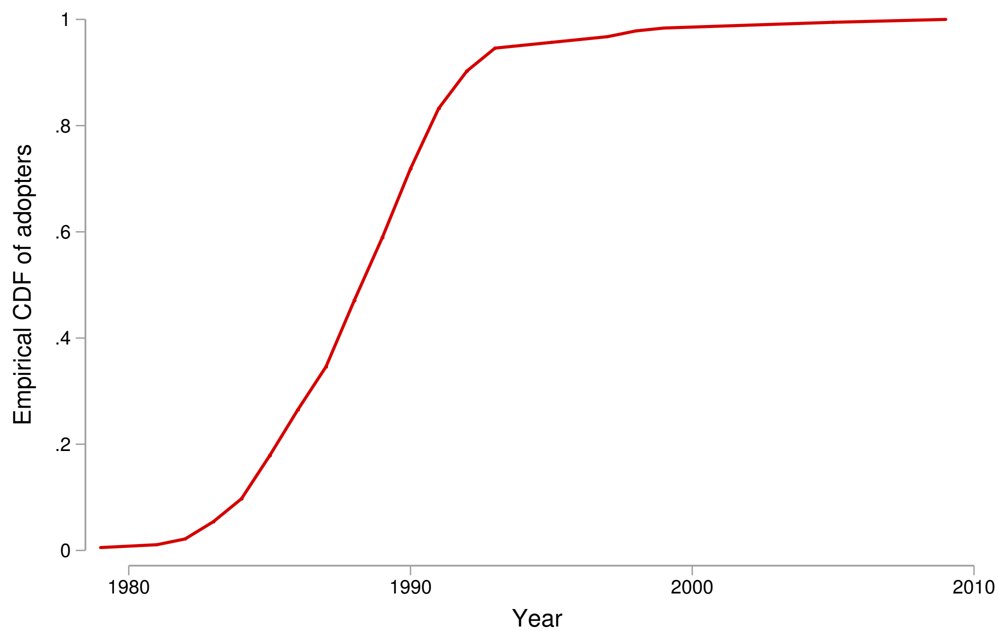
Firm	Compustat gvkey
Ford Motors	4839
General Motors	5073
Dell	14489
Motorola	7585
NCR	7648
Sunrise Medical	10185
Tellelabs	10420
Van Dorn Co	11101
Donnelly Corp	14462
Tuscarora	14578
Selectron	17110
Honeywell Inc	5693
ADC Telecommunications	1013
Sunbeam	1278
Boeing	2285
Campbell	2663
Cascade Corporation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

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

Adopters Dataset

The data for adopters was kindly provided to me by William Wempe from his joint work with Michael Kinney. Xiaodan Gao also provided me with updated data. These data include the years in which a Compustat manufacturer was identified to be a JIT adopter (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 conduct an search of my own and identify an additional 18 firms (reported in Table A2). After linking these identified firm-years to those in my Compustat dataset, I identify a total of 185 adopters in the manufacturing sector. Figure A1 plots the empirical CDF of the adopters in my sample over time.

Figure A1: Adopters, by Year



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

A.2 Local Weather Events

I consider a number of weather events reported by NOAA from 1980-2018. These events are reported at the county level. I keep only weather events that caused at least \$1 million in property damage in a given county and link these local disasters to firm headquarter zip codes.

Using the links provided in Barrot and Sauvagnat (2016), I first map the county-level weather events to firms' headquarter zip codes in Compustat. Following this, I link firms based on their customer-supplier relationships.[14] In the end, I have a dataset of Compustat firm i in industry j with supplier k in year t. I consider weather disasters that hit supplier k's headquarters. The idea is that customer firm i, if it is an adopter, should see a sharper decline in sales growth when its supplier

[14]This is based on a regulation requiring firms to disclose customers representing more than 10% of total reported sales (Financial Accounting Standard Board regulation No. 131).

k's headquarters experiences an unexpected weather event. The regression I run is as follows

$$\text{salegrowth}_{ijt} = \vartheta_1 \text{adopter}_{ijt} + \vartheta_2 \sum_k \text{disaster}_{ijkt} + \vartheta_3 \big[\text{adopter}_{ijt} \times \sum_k \text{disaster}_{ijkt}\big] + \delta_i + \delta_{jt} + \upsilon_{ijt}$$

The coefficient of interest is ϑ_3 which describes the interaction between a JIT adoption indicator and the total number of weather events hitting suppliers of a given firm i. The results are reported in Table 4 in the main text.

A.3 Industry Results

The facts presented in Section 2 are robust to aggregation. Below, I provide evidence that these patterns hold at the four-digit NAICS level.

I begin by estimating

$$\Delta y_{jt} = \gamma \Delta \text{adoptshare}_{jt} + \delta_j + \delta_t + \nu_{jt} \tag{10}$$

where Δy_{jt} refers to the five-year difference in a given outcome for industry j in year t. The specific outcomes considered are inventory-to-sales ratio growth and sales growth. The regressor, $\Delta\text{adoptshare}_{jt}$, denotes the five-year difference in the share of JIT firms residing in a given industry in year t. Table A3 reports the results. For inventory-to-sales growth and sales growth, a one standard deviation increase in the difference in the share of adopters is associated with a change of -8% and 13% of one standard deviation in the outcomes, respectively.

Furthermore, JIT adoption is associated with less variability in outcomes. Figure A2 plots the change in a measure of sales growth variance within an industry against the change in the share of adopters within that industry. The slope of this line is estimated from the following regression

$$\Delta y_{jt} = \gamma \Delta \text{adoptshare}_{jt} + \delta_j + \delta_t + \nu_{jt} \tag{11}$$

The outcome variables specified are five-year differences in the variance of inventory-to-sales growth,

Table A3: Industry-Level Growth Regressions (Five-Year)

Change	Inventory-to-sales growth	Sales growth
Change in adopt share	-0.081***	0.129**
	(0.027)	(0.051)
Fixed effects	Industry, Year	Industry, Year
Observations	2,159	2,159

Note: The table reports panel regression results from Compustat Annual Fundamentals of manufacturing firms (NAICS 31-33). The dependent variables are five-year changes in: inventory-to-sales growth and sales growth. The regressor of interest is the five-year change in share of adopters within a given industry. All variables are standardized, industry and year fixed effects are specified, and standard errors are clustered at the industry level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Table A4: Industry-Level Growth Regressions (Ten-Year)

Change	Inventory-to-sales growth	Sales growth
Change in adopt share	-0.104***	0.093*
	(0.017)	(0.055)
Fixed Effects	Industry, Year	Industry, Year
Observations	2,159	2,159

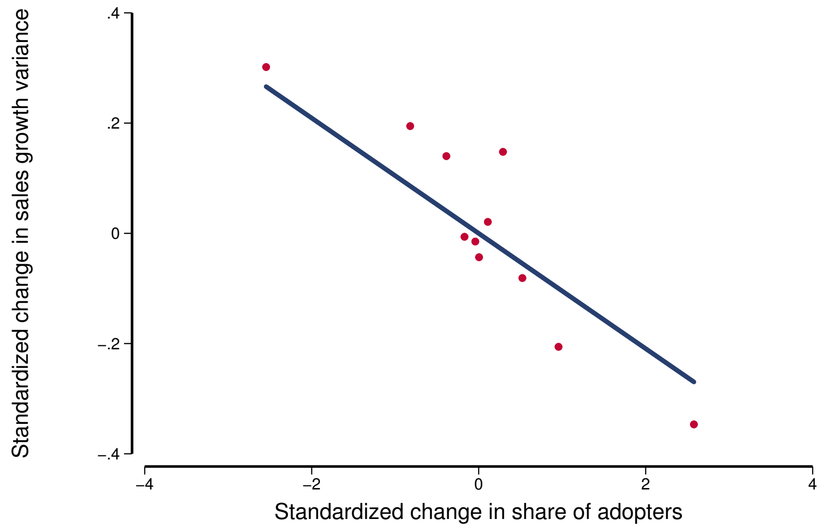
Note: The table reports industry-level panel regression results from Compustat Annual Fundamentals of manufacturing firms (NAICS 31-33). Industries are defined at the 4-digit NAICS-level. The dependent variables are changes in: (1) inventory-to-sales growth and (2) sales growth over a ten-year horizon. The regressor of interest is the change in share of adopters within a given industry over the same horizon. All variables are standardized. Industry and year fixed effects are also specified. Standard errors are clustered at the industry level.

employment growth, and sales growth. Table A5 reports the results. A one standard deviation increase in the share of JIT firms within an industry is associated with a 5%-11% standard deviation reduction in variability of firm outcomes within that industry.

At the same time, industries with more adopters exhibit heightened cyclicality. I show this by running a regression similar to (2) at the industry level. Table A7 reports the results. In an industry comprised of approximately 10% of JIT adopters, an empirically relevant share, industry sales growth tends to rise by 0.7% above the reported baseline.

Regarding sensitivity to weather events, I run a regression similar to (3), however, I achieve

Figure A2: Smoother Outcomes in Industries with More Adoption



Note: The figure displays a binned scatter plot of the normalized five-year difference in sales growth variance against the normalized five-year difference in the share of adopters within an industry.

broader coverage by instead looking at disasters originating at the customer firm's zip code. To this end, I do away with the customer-supplier links and focus on industry-level evidence by running the following regression:

$$\text{salegrowth}_{jt} = \psi_1 \text{adoptshare}_{jt} + \psi_2 \sum_i \sum_k \text{disaster}_{ijkt} + \psi_3 \big[\text{adoptshare}_{jt} \times \sum_i \sum_k \text{disaster}_{ijkt}\big] + \delta_j + \delta_t + v_{jt}$$

Rather than focusing on customer-supplier links, this regression provides evidence that industries with a larger share of JIT adopters appear to be more exposed to local weather disasters. Table A8 reports the results.

Table A5: Industry Level Variance Regressions (Five-Year)

Change	Inventory-to-sales growth	Employment growth	Sales growth
Change in adopt share	-0.053**	-0.080***	-0.112***
	(0.022)	(0.028)	(0.018)
Fixed effects	Industry, Year	Industry, Year	Industry, Year
Observations	2,159	2,159	2,159

Note: The table reports panel regression results from Compustat Annual Fundamentals of manufacturing firms (NAICS 31-33). The dependent variables are five-year changes in interquartile range of (1) inventory-to-sales growth, (2) employment growth, and (3) sales growth. The regressor of interest is the five-year change in share of adopters within a given industry over the same horizon. All variables are standardized. Industry and year fixed effects are also specified. Standard errors are clustered at the industry level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Table A6: Industry-Level Variance Regressions (Ten-Year)

Change	Inventory-to-sales growth	Employment growth	Sales growth
Change in adopt share	-0.068**	-0.082***	-0.115***
	(0.033)	(0.026)	(0.036)
Fixed Effects	Industry, Year	Industry, Year	Industry, Year
Observations	2,159	2,159	2,159

Note: The table reports industry-level panel regression results from Compustat Annual Fundamentals of manufacturing firms (NAICS 31-33). Industries are defined at the 4-digit NAICS-level. The dependent variables are change in interquartile range of: (1) inventory-to-sales growth, (2) employment growth, and (3) sales growth over a ten-year horizon. The regressor of interest is the change in share of adopters within a given industry over the same horizon. All variables are standardized. Industry and year fixed effects are also specified. Standard errors are clustered at the industry level.

Table A7: JIT Adoption and Cyclicality (Industry-Level)

	Sales growth
GDP growth	1.854***
	(0.626)
Adopter share × GDP growth	6.928**
	(3.384)
Adopter × GDP growth	
Fixed Effect	Industry
Observations	3,044

Note: The table reports regression results from Compustat Annual Fundamentals of manufacturing firms (NAICS 31-33). The dependent variable is sales growth and the independent variable of interest is the interaction between the share of JIT firms in an industry and GDP growth. Control variables include logs of sales per worker, firm size, cash-to-assets, and inventory stock, as well as the share of adopters. Standard errors are clustered at the industry level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% signficance.

Table A8: JIT Adoption and Local Disasters (Industry-Level)

	Sales growth
Adopt share	0.011
	(0.017)
Total disasters within industry	-0.0004*
	(0.0002)
Adopt share × Total disasters within industry	-0.007**
	(0.003)
Fixed Effects	Industry, Year
Observations	3,045

Note: The table reports weather event regressions from a sample of Compustat manufacturing firms (NAICS 31-33). The dependent variable is sales growth and the independent variable of interest is the interaction between the share of JIT firms in an industry and total disasters within the industry. Standard errors are clustered at the firm and industry levels respecitvely. *** 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

$$\widetilde{\xi}(z, s, a) = \frac{pqs + V^O(z, s, a) - \widetilde{V}(z, s, a)}{\phi} \tag{12}$$

and

$$\xi^*(z, s, a) = \min\big(\max\big(0, \widetilde{\xi}(z, s, a)\big), \overline{\xi}\big) \tag{13}$$

B.2 Intermediate Goods Firm

The intermediate good firm's problem is

$$\max_{K,L} \left(qK^\alpha L^{1-\alpha} - RK - wL \right)$$

One can solve for K L, and q analytically. In particular, the relative price of the intermediate good is

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

B.3 Equilibrium

An equilibrium is a set of functions

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

such that

1. The household's first order conditions hold

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

2. The intermediate goods firm first order conditions hold

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

3. $V^A, V, V^O, \widetilde{V}$ solve the final good firm's problem

4. Market for final goods clears

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

5. Market for orders clears

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

6. Market for labor clears

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

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

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

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

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

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

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. From 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.

Appendix C Estimation

C.1 Simulated Method of Moments

The parameter vector to be estimated is $\theta = \begin{pmatrix}\rho_z & \sigma_z & \overline{\xi}_{NA} & \overline{\xi}_A & c_s & c_f & c_m & \tau\end{pmatrix}'$. Operationally, this requires solving my plant-level model, given θ, 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.[15] The value of the objective is minimized at 172.61.[16]

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

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

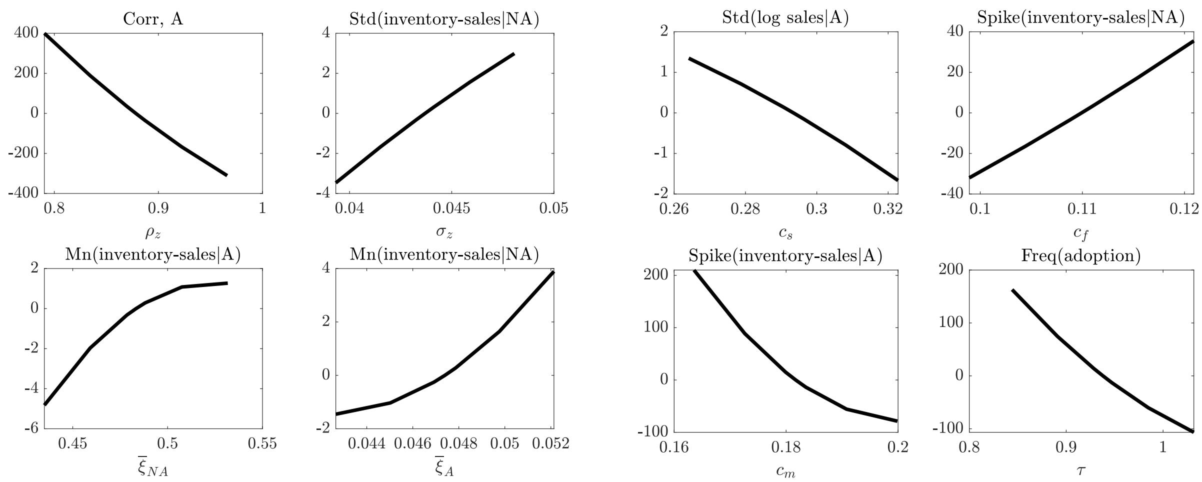
where

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

[15] I specify 100 particles.

[16] Considering all of the data used in the SMM estimation, the J-test of overidentifying restrictions rejects the null hypothesis.

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.[17] 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 ϵ to be a step size of 1.0%.

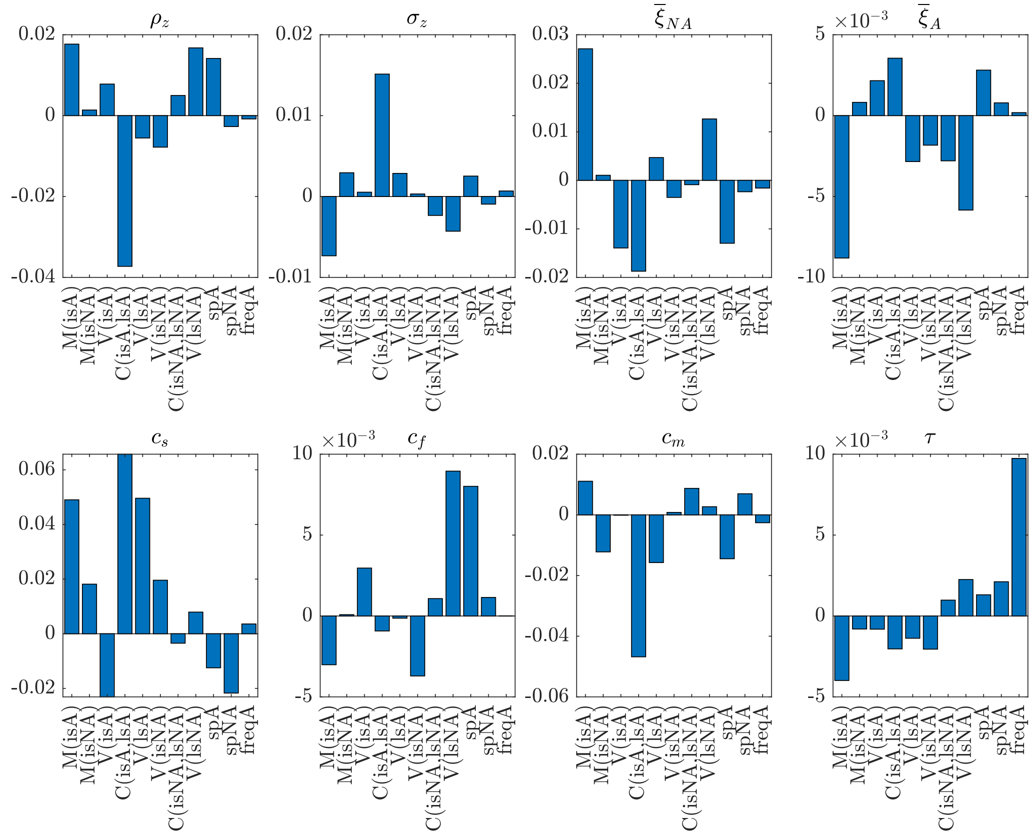
C.2 Identification

The 11 moments jointly determine the eight 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 seven parameters to changes in each of the moments. These results come from an implementation of Andrews et al. (2017). In particular, the sensitivity of $\widehat{\theta}$ to $m(\theta)$ is

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

[17] I simulate 40,000 firms, thereby setting S to be approximately 7.8.

Figure C2: Sensitivity



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

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.

C.3 Estimating Subperiod Model

The counterfactual is estimated using data from 1980-1989. More specifically, I fix all parameters to be as in the estimated full sample adoption model, and re-estimate only the adoption costs, $\{c_s, c_f\}$. Table C1 reports the estimated parameters.

The parameters are estimated precisely. The continuation cost of adoption is higher at around

Table C1: Estimated Parameters (1980-1989 Subperiod)

Description	Parameter	Estimate
Sunk cost of adoption	c_s	0.237
		(0.024)
Continuation cost of adoption	c_f	0.123
		(0.0004)

Note: The table reports the estimated parameters for the 1980-1989 subperiod (standard errors in parentheses). Parameters were estimated by targeting 11 moments. J-test of overidentifying restrictions rejects null hypothesis. Firms in the model are defined to consist of ten plants.

52% of the initial sunk cost relative to the estimated adoption model in the main text. As a result, there is less adoption persistence in the counterfactual model. The steady state of the counterfactual model has a mass of 0.09 adopters, 60% of the mass of adopters in the estimated model. Table C2 reports the model fit. Table C3 reports the full parameterization for the counterfactual model.

C.4 Alternate Counterfactual: Re-estimated Order Costs

The incentives to adopt JIT in the model are governed by adoption costs as well as order costs. As a robustness check to my counterfactual economy, I consider an alternate counterfactual in which I also re-estimate the parameters governing the order cost distributions, $\overline{\xi}_{NA}$ and $\overline{\xi}_{A}$ for the 1980s. I find that the estimated order and adoption costs are little changed from the parameterization in the original counterfactual. Table **??** details the estimated parameters and long-run aggregates of the estimated full sample JIT economy vs. this alternate counterfactual. Comparing these two models, I find that consumption-equivalent welfare rises 0.8% in the JIT model relative to this counterfactual, slightly above the 0.6% increase relative to the counterfactual detailed in the main text. Moreover, I find a comparable contraction amid the disaster: this counterfactual economy contracts by 8.4% amid the same disaster as described in the main text. This amounts to a 1.1 percentage point sharper contraction in the JIT economy, consistent with the headline results.

Table C2: Model vs. Empirical Moments (1980-1989 Subperiod)

Moment	Model	Data
Mean(inventory-sales ratio|adopter)	0.176	0.150
		(0.007)
Mean(inventory-sales ratio|non-adopter)	0.208	0.213
		(0.003)
Std(inventory-sales ratio|adopter)	0.056	0.042
		(0.0004)
Corr(inventory-sales ratio, log sales|adopter)	-0.106	-0.309
		(0.001)
Std(log sales|adopter)	0.218	0.169
		(0.008)
Std(inventory-sales ratio|non-adopter)	0.066	0.070
		(0.0002)
Corr(inventory-sales ratio, log sales|non-adopter)	-0.287	-0.346
		(0.0004)
Std(log sales|non-adopter)	0.277	0.228
		(0.002)
Spike(inventory-sales|adopter)	0.095	0.070
		(0.022)
Spike(inventory-sales|non-adopter)	0.285	0.284
		(0.008)
Frequency of adoption	0.038	0.015
		(0.002)

Note: The table reports the model-based moments and the empirical moments for the estimated 1980-1989 model. Standard errors in parentheses.

Table C3: Counterfactual Parameterization

ρ_z	σ_z	$\overline{\xi}_{NA}$	$\overline{\xi}_A$	c_s	c_f	c_m	τ
0.878	0.044	0.483	0.047	0.237	0.123	0.182	0.938

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

Table C4: Alternate Counterfactual Estimation

Description	Parameter	Estimate
Order cost distribution (non-adopters)	$\overline{\xi}_{NA}$	0.479
		(0.046)
Order cost distribution (adopters)	$\overline{\xi}_{A}$	0.042
		(0.001)
Sunk cost of adoption	c_s	0.229
		(0.043)
Continuation cost of adoption	c_f	0.130
		(0.008)

Note: The table reports the estimated parameters for the alternate counterfactual detailed above (standard errors in parentheses). Parameters were estimated by targeting 11 moments. J-test of overidentifying restrictions rejects null hypothesis. Firms in the model are defined to consist of ten plants.

Table D1: Robustness Parameterization

Parameter	Value	Parameter	Value	Parameter	Value
ρ_z	0.900	$\overline{\xi}_{NA}$	0.600	c_m	0.200
ρ_z	0.750	$\overline{\xi}_{NA}$	0.400	c_m	0.100
σ_z	0.050	$\overline{\xi}_A$	0.055	ΔA	-0.105
σ_z	0.025	$\overline{\xi}_A$	0.040	ΔA	-0.130

Note: The table reports the alternate parameterizations chosen to compute the excess GDP contraction in the JIT economy relative to the counterfactual economy.

Appendix D Robustness

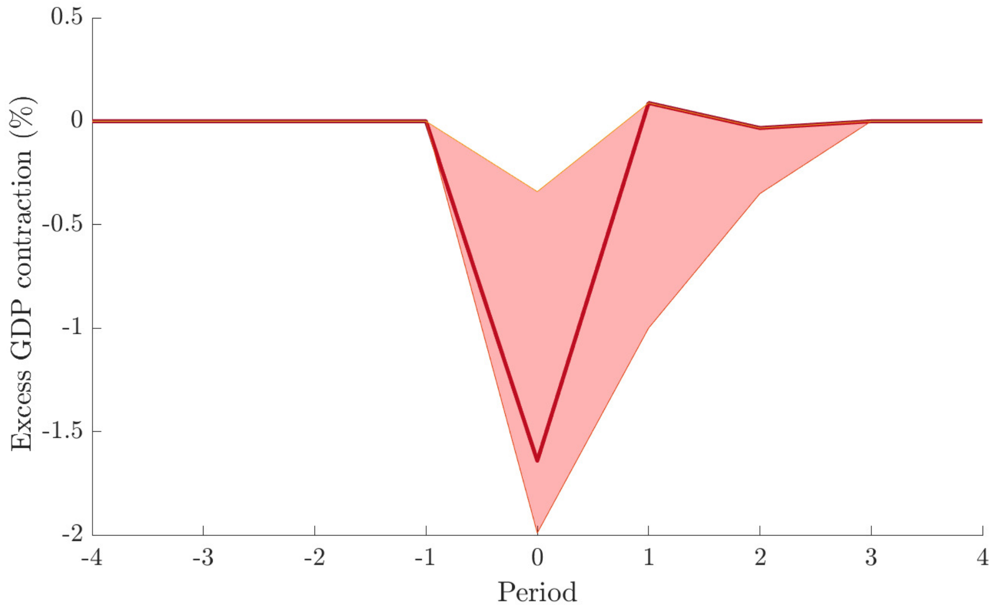
In this section I provide different robustness checks related to the JIT tradeoff presented in the main text. I begin by examining the sensitivity of the tradeoff to different parameter values. I then consider alternate disaster persistence specifications.

D.1 Alternate Parameterizations

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 Figures 8 and 9. Figure D1 plots the gap in GDP growth amid a disaster between the estimated and counterfactual economies. The solid line depicts the figure in the main text while the shaded area captures the different tradeoffs reflected in the alternate parameterizations. Across all specifications, there is a robust negative gap indicating a sharper contraction in the estimated economy relative to the counterfactual.

D.2 Disaster Size

Figure D1: Robustness Checks to Disaster



Note: The figure plots the exceess GDP contraction in the estimated model relative to the counterfactual. The thick solid line refers to the estimated model parameterization used in the main text. The shaded area is obtained by considering the maximal and minimal gap across the two models in each period across the parameterizations detailed in Table D1.

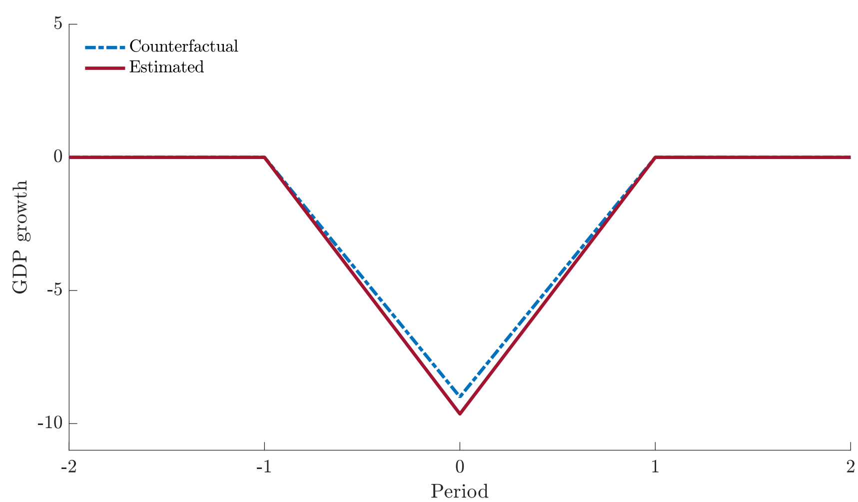
D.3 Alternate Disaster Persistence

Table D2: GDP Contractions by Disaster Severity

Relative shock size	Counterfactual	Estimated	Gap
0.10	-1.22	-1.40	-0.18
0.40	-2.68	-4.10	-1.42
0.50	-3.75	-4.51	-0.76
0.67	-6.16	-6.56	-0.40
1.00	-7.86	-9.50	-1.64
1.15	-10.72	-11.84	-1.12

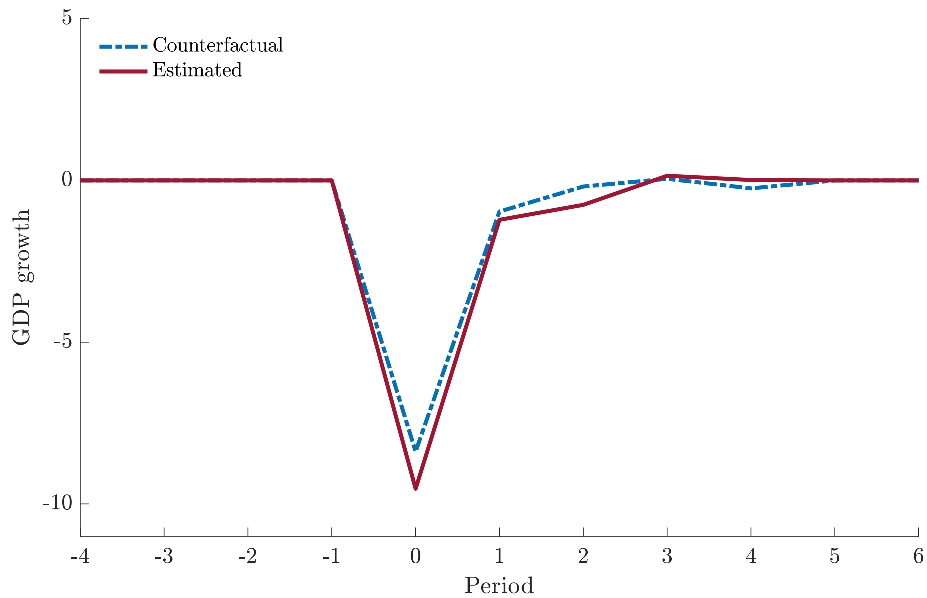
Note: The table reports GDP contractions by disaster size. Column (1) reports the size of the unanticipated shock relative to the baseline shock size reported in the main text (baseline= 1.00). The subsequent columns report the GDP contraction on impact in the counterfactual and estimated economies, respectively as well as the gap in output contractions (estimated minus counterfactual).

Figure D2: One Year Disaster



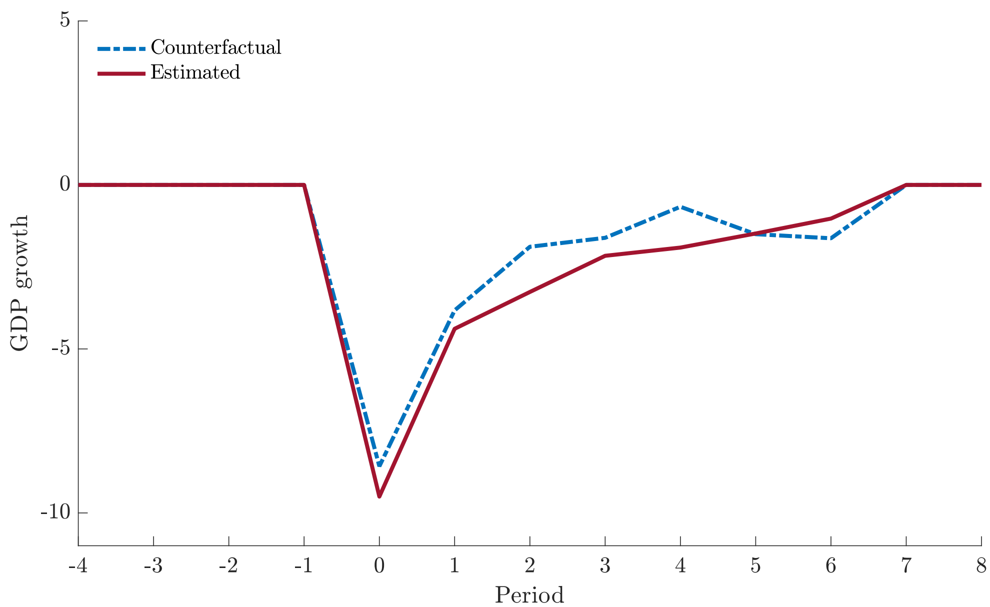
Note: The figure plots the evolution of GDP amid a one year unanticipated disaster episode. The estimated JIT economy contracts 0.6 percentage points further than the counterfactual economy with less JIT.

Figure D3: Five Year Disaster



Note: The figure plots the evolution of GDP amid a five year unanticipated disaster episode. The estimated JIT economy contracts 1.5 percentage points further than the counterfactual economy with less JIT.

Figure D4: Seven Year Disaster



Note: The figure plots the evolution of GDP amid a seven year unanticipated disaster episode. The estimated JIT economy contracts 1 percentage point further than the counterfactual economy with less JIT.