Spread Too Thin: The Impact of Lean Inventories*

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Abstract

Widespread adoption of just-in-time (JIT) production, a strategy that views inventories as inefficient, has reduced inventory holdings. This paper finds that JIT creates a tradeoff between firm profitability and vulnerability to unexpected shocks at the macro level. Empirically, JIT adopters experience higher sales and less volatility while also exhibiting greater cyclicality and heightened sensitivity to natural disasters. I explain these facts in a structurally estimated general equilibrium model where heterogeneous firms can adopt JIT. Relative to a counterfactual economy reflecting adoption patterns from the 1980s, the estimated model implies a 1% increase in long-run firm value. At the same time, an unanticipated COVID-19 shock results in a 1.6 percentage point sharper output contraction. This occurs because, with more JIT, more firms "stock out" while others hoard highly valued materials.

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

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1 Introduction

Up to 70% of manufacturers have reportedly adopted just-in-time (JIT) production, a management philosophy that views inventories as inefficient.[1] Firms adopt JIT in an effort to cut costs associated with managing larger orders and storing idle stocks. Instead, these firms commit to placing smaller more frequent orders from suppliers.[2] Consequently, lean inventory management has contributed to the 11% reduction in aggregate inventory holdings as a share of sales from 1992-2019.[3]

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

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

I first provide firm-level evidence linking the JIT adoption decision to higher firm sales and lower firm volatility. This provides motivating evidence as well as a set of moments that I use when structurally estimating the model. Within firms, JIT adoption is associated with a 16% decrease in inventory-to-sales ratios and a 9% increase in sales. In addition, JIT firms experience an 8-9% decline in employment and sales growth volatility. These empirical results, though not causal, are consistent with positive selection into adoption which subsequently yields firm-level efficiency gains as in my model.

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

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

[3] U.S. Census Bureau, Total Business: Inventories to Sales Ratio [ISRATIO], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/ISRATIO.

I then exploit variation external to the firm and document that JIT adopters are exposed to the business cycle and other unexpected aggregate events. At the firm level, sales growth among JIT firms comoves more closely with GDP growth than non-JIT firms. In addition, JIT adopters experience sharper drops in sales growth when their suppliers face unexpected weather disasters (Barrot and Sauvagnat, 2016). My analysis points to heightened sensitivity among JIT firms upon the realization of external shocks, indicating that an economy composed of more JIT producers is less resilient to such disturbances.

In light of these empirical facts, I build and structurally estimate a dynamic general equilibrium model of JIT production. The model features a 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 a stochastic fixed order cost. JIT firms draw order costs from a distribution that is first order stochastically dominated by those of non-JIT firms. Implementing JIT requires incurring a fixed initial adoption cost and a smaller continuation cost thereafter. In a given period, firms must choose their JIT adoption status, whether to order materials, and how much to produce.

I numerically solve and structurally estimate the model via the simulated method of moments (SMM) based on data from 1980-2018. Relative to a counterfactual economy with less JIT, re-estimated from data during the 1980s, the estimated model yields a welfare gain of 0.6%.[4] In addition, the estimated model delivers a 0.2% increase in measured TFP in the steady state. Intuitively, JIT adoption leads to an economy-wide reduction in fixed order costs which enables adopters to better 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, consistent with the decline observed in the micro data.

Whereas individual adopters benefit from JIT in normal times, the existence of leaner firms renders the economy more vulnerable to unexpected shocks. I consider an unanticipated productivity shock calibrated to match the drop in real US GDP during the onset of the COVID-19 pandemic.

[4]For comparison, this welfare figure lies in the estimated range of welfare costs of business cycles and is similar to the welfare cost of managerial short-termism.

This unforeseen supply chain disruption mimics the nature of the COVID-19 shock, while relating more generally to my empirical evidence on weather disasters.[5]

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 the price of materials makes them more susceptible to stocking out. At the same time, as the price of material inputs rises, inventories are suddenly more highly prized, with an increase in the shadow value of inventories within the firm. As a result, producers that do not fully stock out cut back on material input use in an effort to draw inventories down more slowly. The utilization of fewer material inputs in production in the JIT economy due to stock outs and hoarding leads to a sharper drop in output relative to the counterfactual model.

In short, my empirical and theoretical analysis reveals and quantifies a stark tradeoff between steady state gains 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. In this sense, inventories can serve as a stabilizing force.

Inventory investment has long been of interest to economists as a potential source of macroeconomic volatility.[6] Seminal contributions developed production smoothing models (Ramey and Vine, 2004; Eichenbaum, 1984) and (S,s) models (Scarf, 1960; Caplin, 1985) of inventory investment. Khan and Thomas (2007) elegantly models inventories in a general equilibrium environment with heterogeneous firms and business cycle shocks. The authors find that inventories play little to no role in amplifying or dampening business cycles.[7] My model is similar with the addition of idiosyncratic productivity, an endogenous JIT adoption decision, and a focus on large unanticipated shocks. Moreover Bachmann and Ma (2016) highlights the role that inventories play in a lumpy investment model and argues that inventories can also speak to the macro implications of

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

[6] 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).

[7] 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.

investment with non-convex adjustment costs (Bachmann et al., 2013). I add to our understanding of inventories with a quantitative exercise emphasizing an important tradeoff between micro and macro stability amid unexpected disasters.

In addition, this paper relates to a strand of the management literature that focuses on assessing the gains to JIT. Kinney and Wempe (2002) finds that JIT adopters outperform non-adopters, primarily through profit margins. Nakamura et al. (1998) 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 evidence documented in the management literature and the rich literature on inventories in macroeconomics by highlighting how JIT production matters for aggregate outcomes.

Furthermore, this paper relates to the literature on supply chain disruptions. On the empirical front, I adopt a strategy similar to Barrot and Sauvagnat (2016) to determine whether JIT producers are disproportionately exposed to unexpected weather disasters. Other empirical work has assessed how shocks propagate through a network of firms. For instance, Carvalho et al. (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 relates to models of heterogeneous firms, sunk costs, and supply chains. Meier (2020) models supply chain disruptions in the context of time to build. Moreover, I model the JIT adoption decision in a manner similar to Alessandria and Choi (2007) who model path dependent export decisions. My paper explicitly links supply chain disruptions to an important source of investment at the macro level, inventory accumulation.

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

2 Empirical Patterns Among JIT Firms

Before presenting the model of JIT production, I document empirical evidence that JIT adopters are more efficient and yet are more exposed to external shocks. Furthermore, these facts do not wash out in the aggregate. Appendix A documents that these empirical facts hold at the industry level as well. The evidence speaks to the tradeoff between long-run gains to JIT and the added fragility that characterizes an economy populated by more JIT firms.

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. Specifically, I search for key words such as "JIT," "just-in-time," "lean manufacturing," and "zero inventory." In all, my dataset identifies the years in which approximately 185 Compustat manufacturers adopted JIT.[8] 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.[9]

First, JIT adoption is associated with lower inventory holdings and higher sales.[10] I show this by estimating the following regression

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

where y_{ijt} is an outcome variable for firm i belonging to 6-digit NAICS manufacturing industry j in year t. I specify the outcomes to be log inventory-to-sales ratio and log sales. The regressor of interest, adopter_{ijt}, is a time-varying indicator for whether firm i is a JIT adopter in a given year.

Table 1 reports the regression results. Adopters experience a 16% decrease in inventory-to-

[8] While the information on JIT adoption assuredly precludes any false positives, the limited nature of these documents across the thousands of manufacturers in Compustat leaves open the potential for false negatives in my sample. I account for the possibility of measurement error when modeling JIT by incorporating a parameter that in part governs the observed frequency of adoption. Section 5 discusses this in further detail.

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

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

Table 1: JIT Adoption and Profitability

	(1) Inventory-to-sales	(2) Sales
Adopter	-0.155***	0.092**
	(0.035)	(0.025)
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) based on regression (1). 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 0.68 and 2.15, respectively. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

sales ratios and a 9% increase in sales. The results imply a change of -23% and 4% of one standard deviation in the outcomes, respectively. The regression results allude to the benefits of JIT in the model. Facing lower fixed order costs, adopters hold fewer inventories in favor of placing smaller more frequent orders. Since they store fewer inventories, adopters also incur fewer carrying costs. These cost reductions lead adopters to allocate more resources to production.

Second, JIT adopters experience less micro volatility. I re-estimate (1) where y_{ijt} now denotes a rolling 5-year standard deviation of sales growth and employment growth for firm i in industry j in year t. Table 2 reports the results. Adopters see an 8% decline in employment growth volatility and a 9% decline in sales growth volatility. This is consistent with the stabilizing role that JIT plays in the model. As firms smooth out their inventory cycles due to the lower fixed order costs, they moderate the variability of other outcomes as well.

I next document facts relating to firm-level exposure brought on by JIT, exploiting aggregate variation and examining sensitivity to a set of specific events such as macro fluctuations and weather disasters. The regression results accord with the model in that adopters are less insured against unanticipated disruptions, and an economy with more JIT firms is more exposed to aggregate shocks.

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

Table 2: JIT Adoption and Variance of Outcomes

	(1) Employment growth	(2) Sales growth
Adopter	-0.079*	-0.087**
	(0.041)	(0.032)
Fixed effects	Firm, Industry × Year	Firm, Industry × Year
Observations	16,055	16,055

Note: The table reports panel regression results from Compustat Annual Fundamentals of manufacturing firms (NAICS 31-33) based on regression (1). The regressor of interest is the firm-year adoption indicator. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

with GDP growth

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

where $\mathbf{X}$ denotes a set of controls that include sales per worker, firm size, cash holdings, and cost of goods sold-to-sales. The coefficient γ_3 measures the extent to which firms exhibit more cyclicality. Table 3 reports the regression results. Based on column (1), a 1% increase in GDP growth is associated with a roughly 1% increase in sales growth among non-adopters. Adopters experience an additional sales growth increase of 0.7% above this baseline. After also controlling for industry trends, I find that adopters are about 50-70% more cyclical than non-adopters.

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

$$y_{ijt} = \psi_1 \text{adopter}_{ijt} + \psi_2 \text{disaster}_{ijt} + \psi_3 \big[\text{adopter}_{ijt} \times \text{disaster}_{ijt}\big] + \mathbf{X}'_{ijt}\beta + \delta_{jt} + \delta_i + \varepsilon_{ijt}. \tag{3}$$

The disaster_{ijt} variable denotes the log of total upstream disasters faced by firm i residing in industry j in year t. I collect information on weather disasters from NOAA and link these disasters to a firm's upstream suppliers' zip codes via the aforementioned Barrot and Sauvagnat (2016) links.

Table 3: JIT Adoption and Cyclicality

	Sales growth	Sales growth
GDP growth	1.017***	
	(0.070)	
Adopter × GDP growth	0.710***	0.476*
	(0.197)	(0.271)
Controls	Yes	Yes
Fixed Effect	Firm, Industry	Firm, Industry × Year
Observations	32,881	28,665

Note: The table reports regression results from Compustat Annual Fundamentals of manufacturing firms (NAICS 31-33) based on regression (2). The independent variable of interest is the interaction between the adopter indicator and GDP growth. Control variables include logs of sales per worker, firm size, cash-to-assets, and cost of goods-to-sales, as well as the adoption indicator. Column (1) reports results without year fixed effects. Column (2) includes year fixed effects. Standard errors are clustered at the firm level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% signficance.

The control variables specified in $\mathbf{X}$ include the number of upstream suppliers as well as a set of controls (sales per worker, cost of goods sold-to-sales, and inventory-to-sales) for the downstream firm and for the average of its upstream suppliers.

Table 4 reports the estimation results. Consistent with Table 1, adopters tend to be more profitable. Moreover, 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, a roughly 16% standard deviation decrease. Adopters experience an additional 4 percentage point drop, making them more than twice as sensitive to upstream disasters as non-adopters.

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

Table 4: JIT Adoption and Sensitivity to Local Disasters

	Sales growth
Adopter	0.104***
	(0.030)
Total upstream disasters	-0.032*
	(0.018)
Adopter $\times$ Total upstream disasters	-0.044**
	(0.019)
Fixed Effects	Firm, Industry $\times$ Year
Observations	1,192

Note: The table reports weather event regressions from a sample of Compustat manufacturing firms (NAICS 31-33) based on regression (3). The independent variable of interest is the interaction between the adoption indicator and total number of upstream disasters. Control variables include number of upstream suppliers and sales per worker, cost of goods-to-sales, and inventory-to-sales for both the downstream firm and its average upstream supplier. Standard errors are clustered at the firm level. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

3 A Model of Just-in-Time Production

Having illustrated the essence of the tradeoff in the data, I next build the full general equilibrium model which will provide quantitative statements about the implications of JIT. The model is similar in spirit to Khan and Thomas (2007) and Alessandria and Choi (2007), embedded with JIT and ultimately incorporating large unanticipated disasters rather than traditional business cycle shocks.

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

The representative household is endowed with one unit of time in each period and values consumption and leisure according to the following preferences:[11]

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

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

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

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 materials using capital K_t and labor L_t according to:

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

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

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

where q_t denotes the price of the intermediate good.

Finally, a continuum of final goods firms produce using materials, m_t, and labor, n_t, according

[11] Rogerson (1988) microfounds these preferences in a model of indivisible labor and lotteries. These preferences provide tractability and are common in the literature, e.g. Gilchrist et al. (2014); Ottonello and Winberry (2020); Senga (2018).

a decreasing returns to scale technology:

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

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

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

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

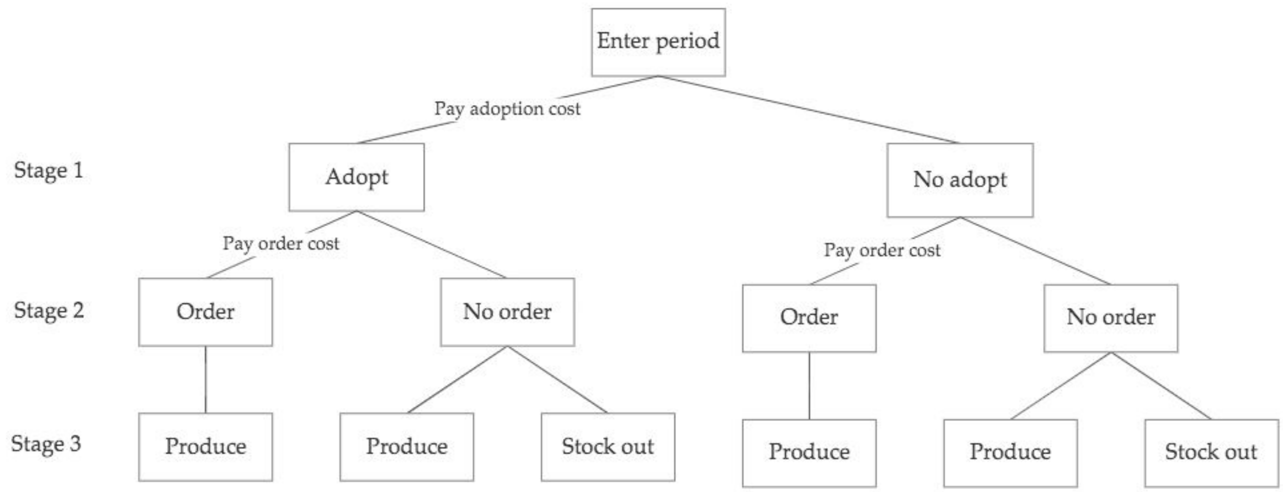
Figure 1 details the final goods producers' decision-making timeline. Each period is broken into three stages. A producer enters the period with realized productivity, z_t, inventory stock, s_t, and adoption status, a_t. In the first stage, the producer decides whether or not to adopt JIT. If a producer does not enter the period as a continuing adopter, it must pay c_s in order to initially adopt. Alternatively, if the producer enters the period as an adopter, it must pay a smaller continuation cost $c_f < c_s$ in order to maintain its status as a JIT adopter.

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

In the next stage, producers learn their order cost, $\xi \sim U(0, \overline{\xi})$, and decide whether or not to place an order, o_t. JIT producers face a more favorable order cost distribution, $\overline{\xi}_A < \overline{\xi}_{NA}$. Lastly, following the adoption and the order decisions, final goods producers decide how much to produce.

I characterize the final goods firms' problem in terms of inventory stocks rather than specific order or material input choices. In particular, if a firm enters the period with inventory stock s_t,

Figure 1: Decisions of Final Goods Firms



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

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 and endogenous prices, p, q, and w. The firm first decides whether to adopt JIT. Note that the adoption status is a binary outcome. The value of adopting is:

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

where

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

and $V^O(z, s, a, \xi)$ refers to the firm's value in the second stage. 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 in the second stage is[12]

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

where the value of placing an order is

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

and $V^P(z, s, a)$ is defined below. 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

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

Stage 3: Production Decision

Upon making an adoption decision and choosing whether to place an order, and if so what size, the firm decides how much to produce. Suppose that a firm enters this stage with inventory stock $\widetilde{s}$

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

such that:

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

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

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

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.

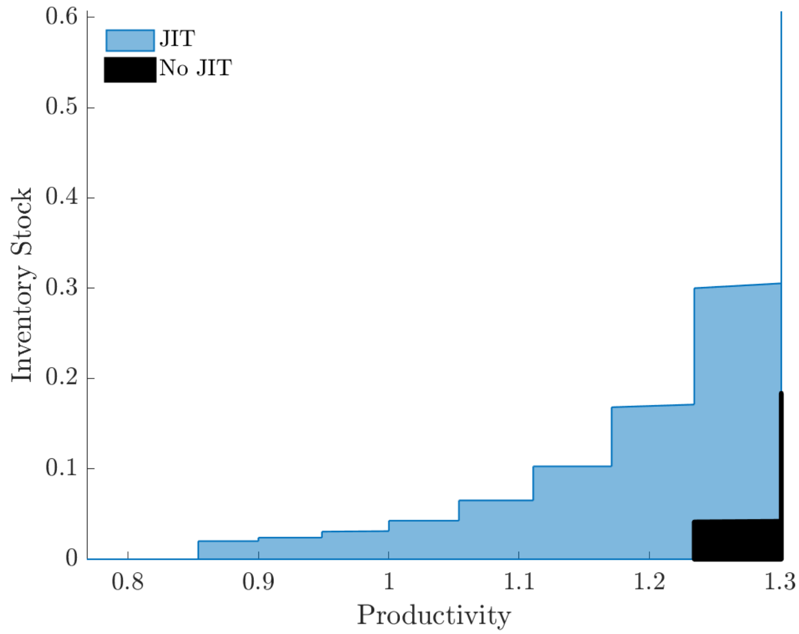
A final goods producer is said to stock out if it enters the period with no inventories, $s = 0$, and chooses to not place an order. Without inventories the firm has no material inputs to make use of in the production stage. As a result, it foregoes production in that period, but can restart production in the future conditional on a favorable order cost draw.

4 Analyzing the Model

The endogenous adoption decision allows the model to replicate important features of the data, namely, higher profitability and reduced micro volatility among JIT firms. Since implementing JIT comes at a relatively large sunk cost, not all firms optimally choose to adopt JIT. Figure 2 plots the adoption frontiers for JIT and non-JIT producers. The black shaded area by the bottom right corner represents the region of the state space in which non-JIT firms choose to adopt JIT.

At the same time, a producer is likely to remain an adopter conditional on already being one. This is because the continuation cost of retaining JIT is smaller than the initial sunk cost. Hence, the endogenous adoption decision exhibits persistence. The larger blue shaded area of Figure 2

Figure 2: Adoption Frontiers

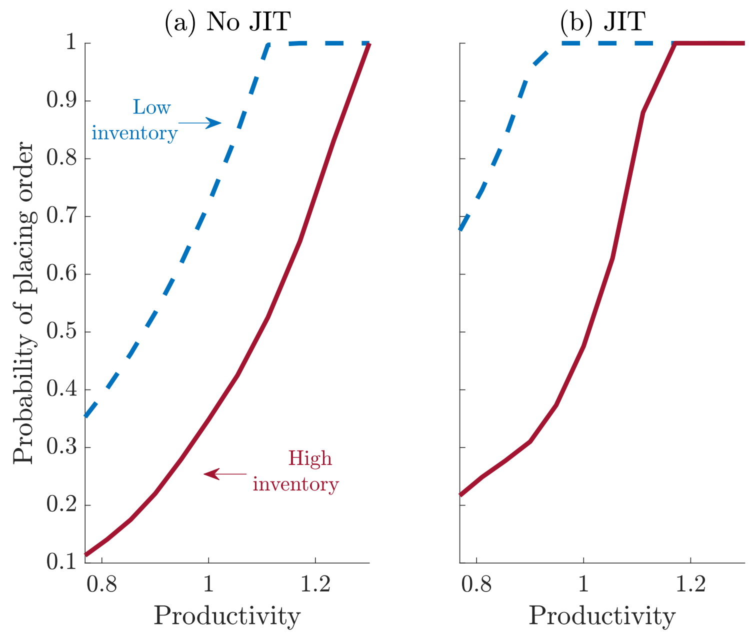


Note: The figure plots the adoption frontier among JIT and non-JIT firms. The blue area plots the region of the state space in which existing JIT firms choose to remain adopters. The black shaded area reflects the region of the state space in which non-JIT firms select into adoption.

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, the decision to adopt JIT reflects a favorable productivity realization which, when coupled with lower average order costs, leads firms to reduce inventory stocks and incur fewer carrying costs thereby generating more output.

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

Figure 3: Order Probabilities

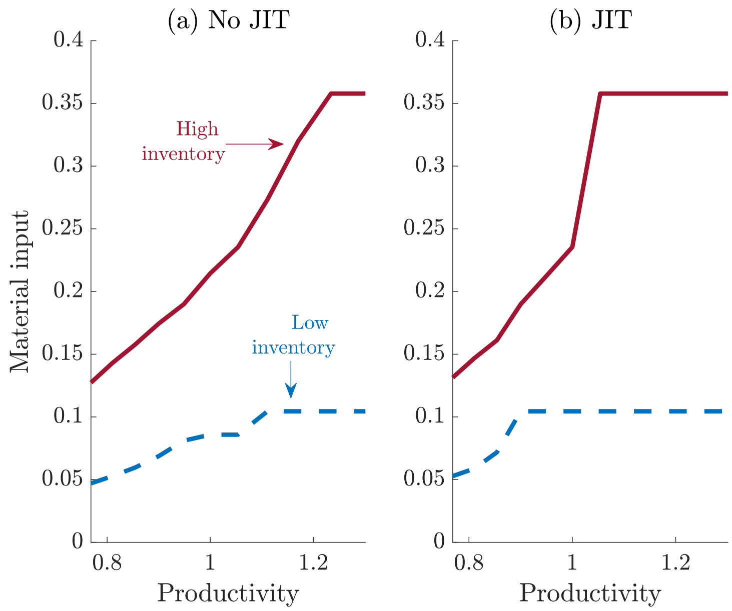


Note: The figure plots the probability of placing an order in the order stage as a function of productivity. Panel (a) plots the probabilities among non-adopters and panel (b) plots the probabilities for adopters. The solid red line reflects a high inventory establishment in the model while the dashed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

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 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. Both the order threshold and the material input policy reflect a treatment effect that allows firms to produce at lower costs which in turn raises firm sales following adoption.

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

Figure 4: Material Usage



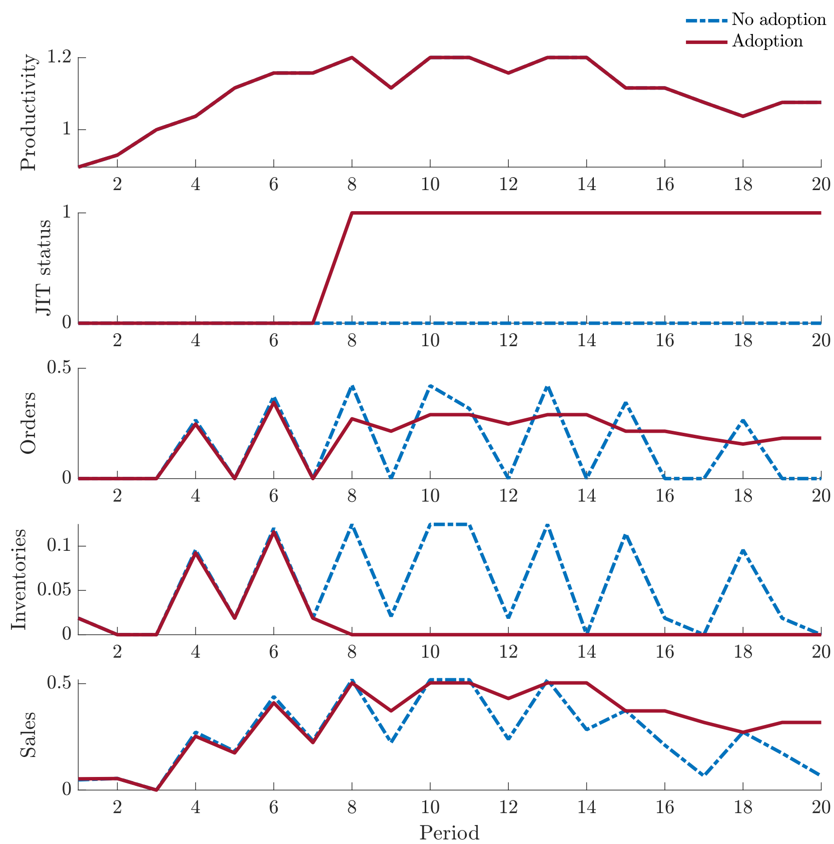
Note: The figure plots material usage policy functions in the production stage as a function of productivity. Panel (a) plots the policy among non-adopters and panel (b) plots the policy for adopters. The solid red line reflects a high inventory establishment in the model while the dashed blue line reflects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

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

Furthermore, upon adopting JIT, the plant's simulated path for orders is smoothed considerably relative to the economy without adoption. This illustrates the insight that JIT mutes the inventory cycle. Because adopters face lower fixed order costs, their target inventory stocks are lower in the JIT model and the frequency of placing an order increases. The smoother path for orders also smooths firm sales which can explain the lower variance of outcomes among adopters in the data.

The fourth panel of the figure, however, points to the source of exposure to unexpected shocks. Since adopters hold little to no inventory stocks, an unanticipated supply chain disruption that prevents the establishment from acquiring materials in a given period will disrupt its production pro-

Figure 5: Adoption Mutes the Inventory Cycle



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

cess. On the other hand, the same plant in the no JIT economy will on average have a larger buffer of inventories from which to draw when producing amid such an event.

5 Structural Estimation

I structurally estimate the model using the micro data analyzed in Section 2. The estimated model captures important features of the firm-level data including the adoption frequency, levels of and covariances between inventories and sales, and spikes in inventory holdings. Importantly, the es-

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.

timated model allows me to quantify 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.[13]

Of the 13 model parameters listed in Tables 5 and 6, 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.

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

[13] 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.

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; Bazdresch et al., 2018). This is done by computing a set of targeted moments in the model and minimizing the weighted distance between the empirical moments and their model-based analogs.

Specifically, I target 11 moments to estimate the 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 which deliver three moments, and the frequency of positive inventory-to-sales ratio spikes, defined as instances in which the inventory-to-sales ratio exceeds 0.25.[14] I specify the asymptotically efficient choice of the weighting matrix which is the inverse of the covariance matrix of the moments.

5.2 Informativeness of Moments

The choice of moments is crucial for the identification of the parameters, so I discuss their informativeness in turn. While targeted moments jointly determine the parameters to be estimated, there are nonetheless certain moments that are especially informative in pinning down a given parameter.

Idiosyncratic productivity persistence informs the covariance between inventory-to-sales and log sales among adopters. An increase in ρ_z implies that a firm with a favorable productivity realization will select into adoption, reduce its inventory holdings due to the lower average fixed order costs and observe higher sales. As a result, the covariance between inventory-to-sales and log sales among adopters becomes more negative. Moreover, idiosyncratic productivity dispersion informs variances, for instance the variance of inventory-to-sales among non-adopters, as an increase in σ_z results in more dispersed outcomes among producers.

Furthermore, an increase in the order cost distribution for non-adopters raises the inventory-to-

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

sales ratio for JIT firms. Intuitively, higher order costs among non-JIT producers expands the area representing the adoption frontier for non-JIT producers in Figure 2, leading more firms to select into adoption. 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 returns to continued adoption fall leading less productive and more bloated producers abandon JIT thereby raising inventory-to-sales ratios among non-adopters.

An increase in the sunk cost of adoption reduces the variance of log sales among adopters since higher initial sunk cost of adoption reduces the adoption frontier among non-JIT producers. As a result, the pool of adopters is composed of more similar and productive producers who collectively face less variable outcomes. An increase in the continuation cost of adoption reduces the scope for remaining a JIT producer. More bloated, less productive firms will therefore abandon JIT, leading to an increase in spike rates among non-adopters. On the other hand, an increase in the carrying cost of inventories leads all firms to lean out, thereby reducing spike rates. Finally, a rise in the the share of observed non-adopters reduces 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 estimated technology parameters, ρ_z and σ_z, are consistent with parameterizations in the literature (Khan and Thomas, 2008; Hennessy and Whited, 2007; Meier, 2020), collectively ranging from 0.68-0.89 and 0.02-0.12 respectively. My estimates imply a more persistent and less dispersed idiosyncratic productivity process than that estimated in Clementi et al. (2015) which is likely due to the fact that my sample consists of publicly traded Compustat manufacturers who are larger and older than the

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)	$\overline{\xi}_{NA}$	0.483
		(0.029)
Order cost distribution (adopters)	$\overline{\xi}_A$	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.

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, 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.

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.

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.

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 years of my sample,

Table 8: Model-Based Regressions

Panel A: Levels		
	Inventory-to-sales	Sales
Data	-0.155	0.092
Estimated	-0.142	0.098
Counterfactual	-0.165	0.123
Panel B: Volatility		
	Employment growth	Sales growth
Data	-0.079	-0.087
Estimated	-0.099	-0.087
Counterfactual	-0.117	-0.098

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.

1980-1989, 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.[15]

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 reductions in inventory-to-sales ratios. The OLS coefficients from both models reside within the 95% confidence interval

[15] 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.

for the point estimate in the data of -0.155. In addition, the estimated and the counterfactual models both predict an increase in sales among adopters, with the estimated model delivering a closer match to the empirical coefficient. Moreover, both models predict reductions in firm volatility among adopters, with the estimated model providing a closer fit to the coefficient of employment growth volatility and an exact match to sales growth volatility. 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.

6 Quantifying the Tradeoff

Having estimated the model, I proceed to quantify the tradeoff between the long-run gains to JIT and the vulnerability to unanticipated disasters that JIT exposes. I first examine the model's steady state to characterize the benefits of lean production. I then analyze the dynamics of the estimated economy following a COVID-19 disaster.

6.1 Steady State

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

As expected, inventory holdings fall in the estimated model. The reduction in inventories is due to a decrease in target inventory stocks across all firms. Relative to the counterfactual, the estimated model delivers a roughly 11% decline in the real aggregate inventory-to-sales ratio, a figure that can account for 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

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	

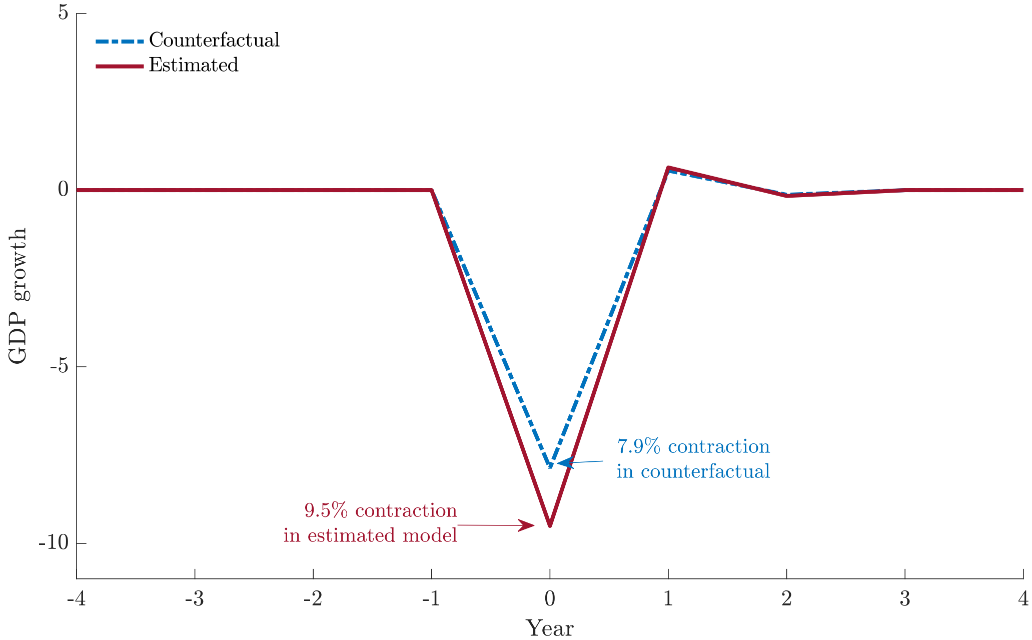
Note: The table reports steady state values of the estimated model relative to the counterfactual model, in percent deviations. Panel A reports the levels of aggregates. Panel B reports measures of firm volatility from unconditional simulation of 40,000 firms over 50 periods.

terms, a magnitude comparable to the costs of business cycles (Krusell et al., 2009) and the costs of managerial short-termism (Terry, 2017).

Fixed order costs are a source of misallocation in the model. Ideally firms would like to hold no material inventories, instead placing orders and fully utilizing them when producing every period. In an effort to minimize the number of times the fixed order costs are incurred, producers hold non-zero inventories. For this reason, the estimated JIT adoption model implies a reduction in 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 producers. In essence, firms place more frequent orders and therefore have the flexibility to better align their material usage with their realized micro productivity realizations. The estimated model implies that JIT adoption raises measured TFP by approximately 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.

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.

6.2 Effects of an Unanticipated Disaster

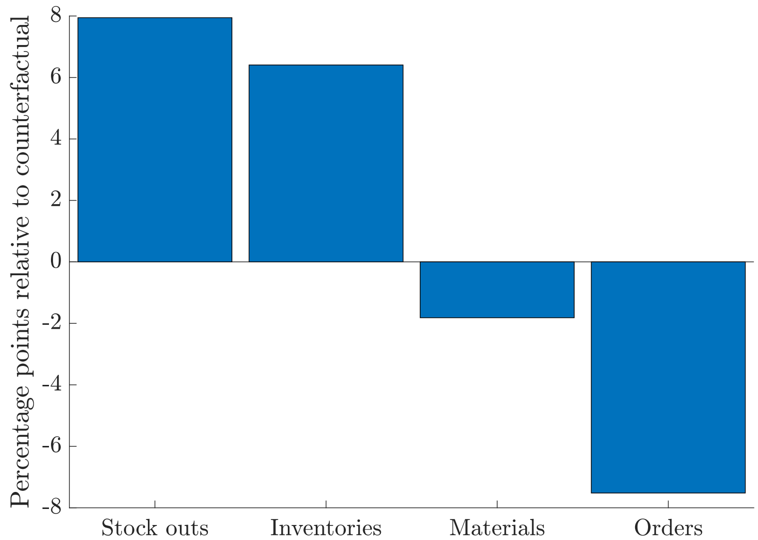
I next show that despite enjoying higher profits and smoother firm-level outcomes, an economy populated by lean producers is more vulnerable to an unexpected disaster. To do this, I introduce aggregate productivity into the production function for intermediate goods.

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

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 2020. I consider a disaster duration such that the economy returns to its steady state after three years.[16] Figure 6 displays the endogenous output response to this unexpected disaster. In addition,

[16]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

Figure 7: More Stock Outs and Inventory Hoarding



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

Figure 7 reports the key differences in endogenous responses between the two models over the full disaster path.

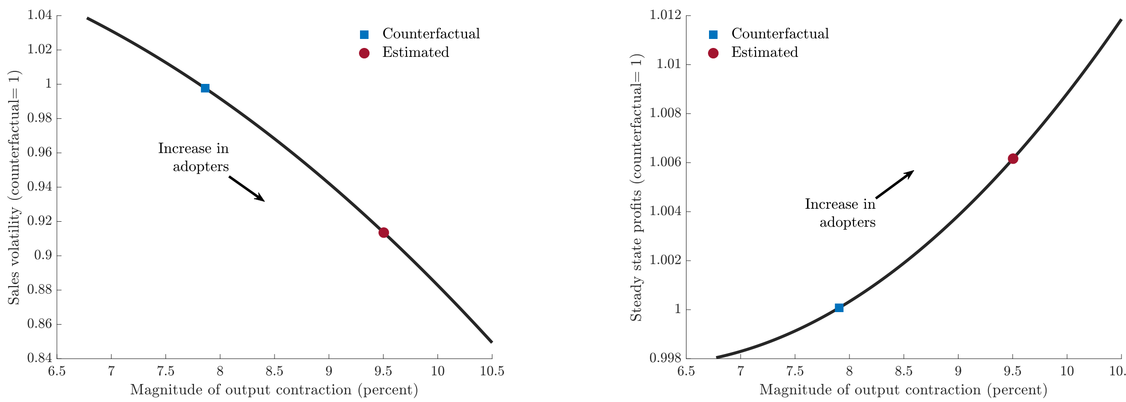
Overall, the estimated model sees a 1.6 percentage point sharper output contraction on impact than the counterfactual model. During an unexpected disaster, the shadow value of inventories rises leading firms to reduce order sizes. Since firms in the JIT economy are leaner on average, the JIT economy 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 therefore contract more sharply in the JIT model. In particular material input 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 sub-

alternate durations in Appendix D with little impact on the qualitative conclusions.

Figure 8: Micro Stability vs. Macro Vulnerability

(a) Sales Volatility (b) Firm Profits



Note: Panels (a) and (b) plot the magnitude of GDP contraction conditional on a 3-year disaster on the horizontal axis. Panel (a) plots an index of equilibrium firm sales volatility on the vertical axis (relative to the counterfactual economy defined above) while Panel (b) plots an index of equilibrium firm profits on the vertical axis (relative to the counterfactual economy defined above). Each point represents a different counterfactual economy, with the estimated economy denoted by the red circle and the counterfactual described in the text denoted by the blue square. 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.

stantial 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.[17] Lean inventory management therefore plays a meaningful role in determining the vulnerability of the economy to unanticipated shocks. During large unexpected disasters, inventories can in fact serve as a stabilizing force.

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 frontiers that illustrate the micro-macro tradeoff associated with JIT for a range of counterfactual economies. These frontiers point to an economically important tradeoff and imply that inventory management is an important source of

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

aggregate fluctuations amid large unexpected shocks.

Panel (a) of Figure 8 plots the tradeoff between firm sales volatility 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 panel 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.

Panel (b) of Figure 8 plots a similar tradeoff, this time comparing 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% 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 the benefits of JIT inventory management among publicly traded manufacturers. Upon adopting JIT, firms hold fewer inventories, and observe higher sales and smoother outcomes. JIT firms, however, 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 firm value by 1% and reduces firm volatility by 9%. At the same time, JIT elevates firm vulnerability due to low inventory buffers. Amid an unexpected disaster, output in the estimated JIT economy contracts 1.6 percentage points more than a counterfactual economy with less JIT. Adoption, therefore, gives rise to a highly important and previously undocumented tradeoff. Economists interested in understanding fluctuations within firms, and the responsiveness of the economy to aggregate shocks, should play close attention to both inventories and management practices.

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Appendix A Empirics

This section provides summary statistics of the data used in Section 2 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

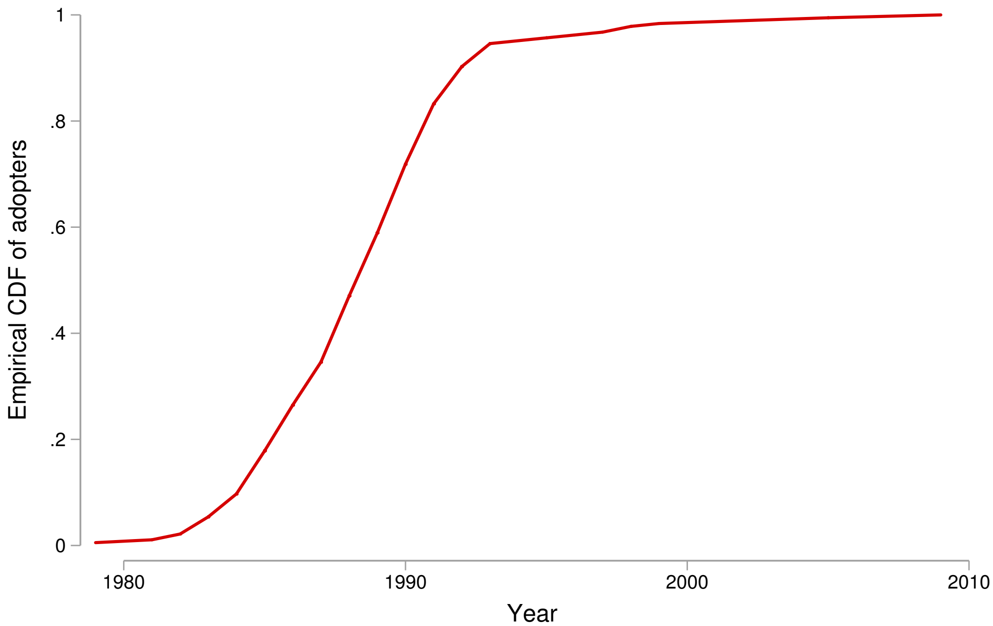
Firm	Compustat gvkey
Ford Motors	4839
General Motors	5073
Dell	14489
Motorola	7585
NCR	7648
Sunrise Medical	10185
Tellelabs	10420
Van Dorn Co	11101
Donnelly Corp	14462
Tuscarora	14578
Selectron	17110
Honeywell Inc	5693
ADC Telecommunications	1013
Sunbeam	1278
Boeing	2285
Campbell	2663
Cascade Corporation	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.[18] 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

[18] 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

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

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. I consider the log the inventory-to-sales ratio and log sales as the outcomes of interest. 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 21% 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	Sales
Change in adopt share	-0.081**	0.207***
	(0.035)	(0.069)
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 logs of inventory-to-sales and sales. 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 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

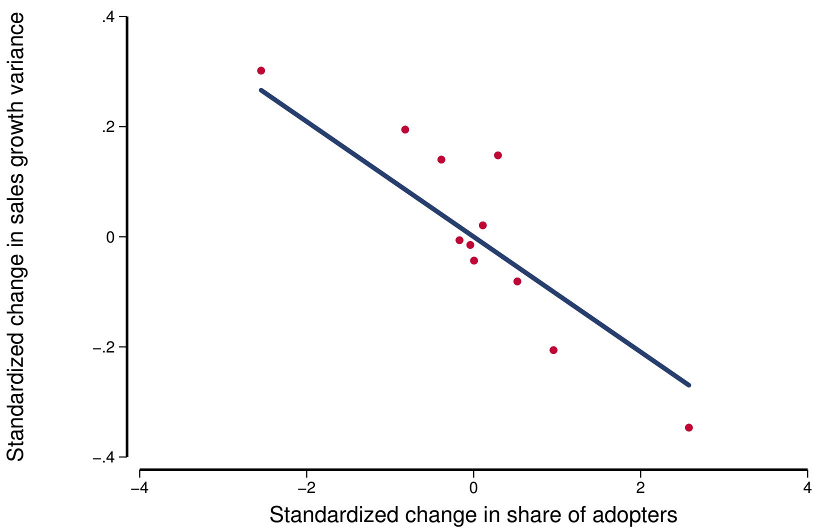
Note: The table reports panel regression results from Compustat Annual Fundamentals of manufacturing firms (NAICS 31-33). The dependent variables are five-year changes in interquartile range of (1) inventory-to-sales growth, (2) employment growth, and (3) sales growth. The regressor of interest is the 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.

employment growth, and sales growth. Table A4 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 A5 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 broader coverage by instead looking at disasters originating at the customer firm's zip code. To this

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.

Table A5: JIT Adoption and Cyclicality (Industry-Level)

	Sales growth	Sales growth
GDP growth	1.854***	
	(0.626)	
Adopter share × GDP growth	6.928**	7.568*
	(3.384)	(3.851)
Fixed Effect	Industry	Industry, Year
Observations	3,044	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.

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 A6 reports the results.

Table A6: 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

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

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

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

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^O, V^*, V^P 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

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

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

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 $\theta = \left(\rho_z \;\; \sigma_z \;\; \overline{\xi}_{NA} \;\; \overline{\xi}_A \;\; c_s \;\; c_f \;\; c_m \;\; \tau\right)'$. 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.[19] [20]

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

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

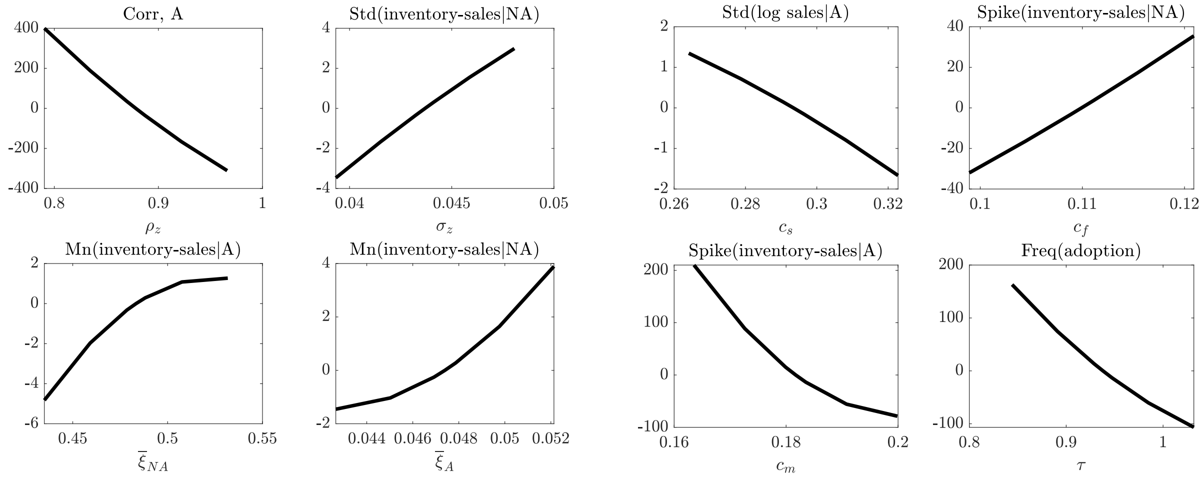
where

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

[19] I specify 100 particles.

[20] Considering all of the moments used in the overidentified 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.[21] 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%.

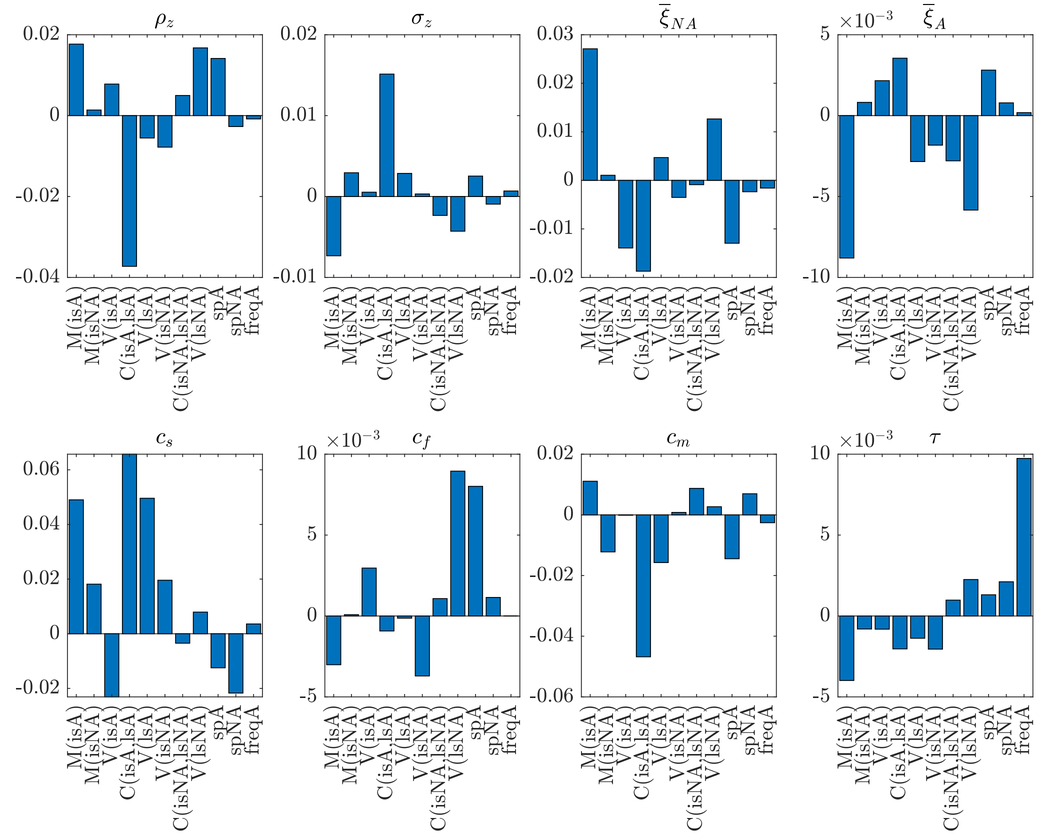
C.2 Identification

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

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

[21] 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	$\bar{\xi}_{NA}$	0.600	c_m	0.200
ρ_z	0.750	$\bar{\xi}_{NA}$	0.400	c_m	0.100
σ_z	0.050	$\bar{\xi}_A$	0.055	ΔA	-0.105
σ_z	0.025	$\bar{\xi}_A$	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

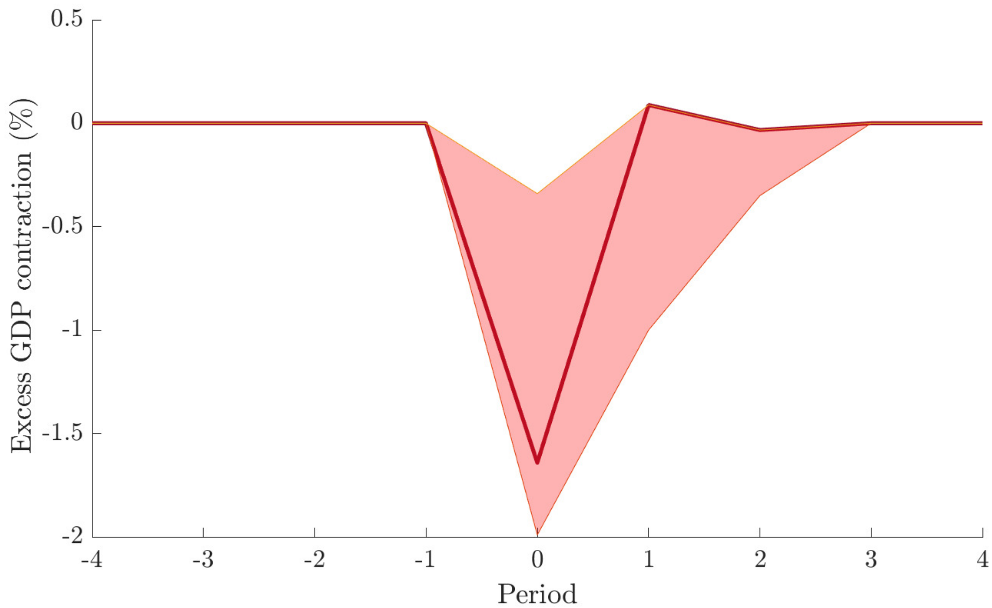
In this section I provide different robustness checks related to the JIT tradeoff presented in the main text. I begin by examining the sensitivity of the tradeoff to different parameter values. I then consider alternate disaster persistence specifications.

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 **??** and **??**. 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.

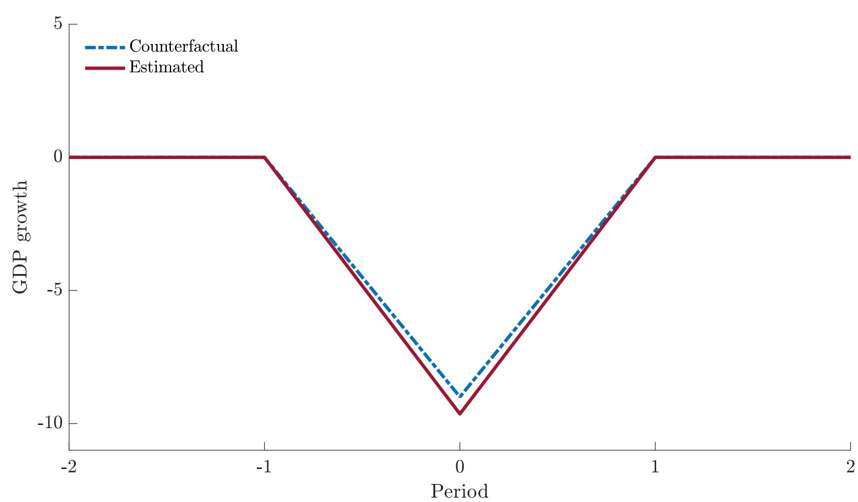
D.3 Alternate Disaster Persistence

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

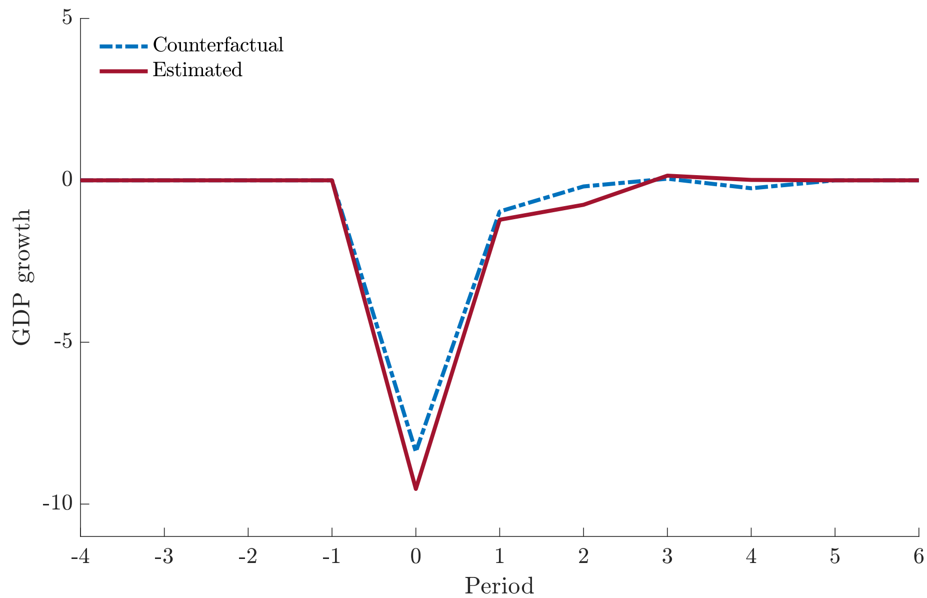
Note: The table reports GDP contractions by disaster size. Column (1) reports the size of the unanticipated shock relative to the baseline shock size reported in the main text (baseline= 1.00). The subsequent columns report the GDP contraction on impact in the counterfactual and estimated economies,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

Figure D2: One Year Disaster



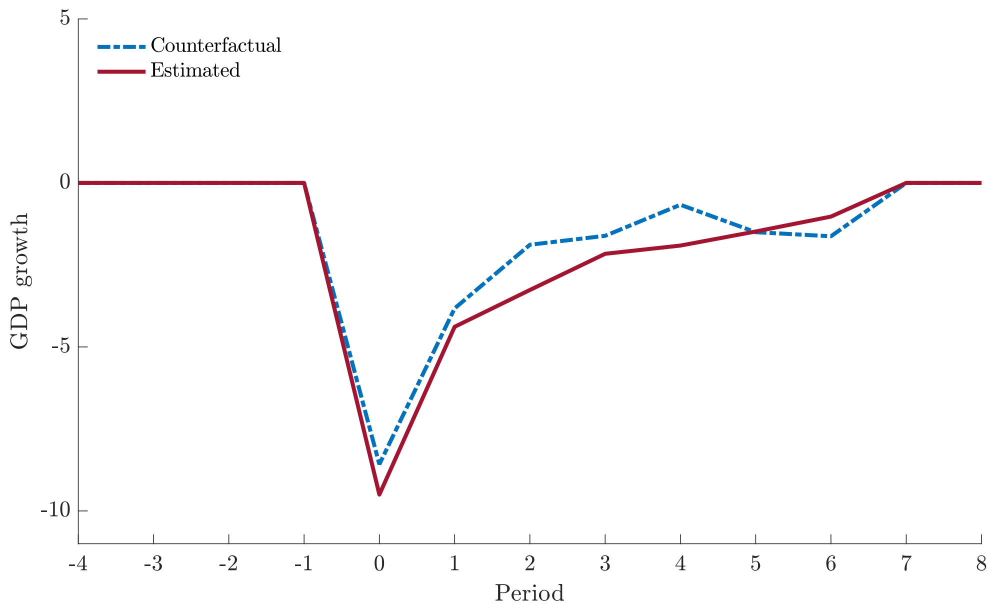
Note: The figure plots the evolution of GDP amid a one year unanticipated disaster episode. The estimated JIT economy contracts 0.6 percentage points further than the counterfactual economy with less JIT.

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.