Macroeconomic and Asset Pricing Effects of Supply Chain Disasters*

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September 21, 2022

Abstract

We build a general equilibrium production-based asset pricing model with heterogeneous firms that jointly accounts for firm-level and aggregate facts emphasized by the recent macroeconomic literature, and for important asset pricing moments. Using administrative firm-level data, we establish empirical properties of large negative idiosyncratic shocks and their evolution. We then demonstrate that these shocks play an important role for delivering both macroeconomic and asset pricing predictions. Finally, we combine our model with data on the universe of U.S. seaborne import since 2007, and establish the importance of supply chain disasters for the cross-section of asset prices.

*We thank Hengjie Ai, Gianluca Benigno, Andrew Chen, Andrea Frazzini, Stefano Giglio, Urban Jermann, Yukun Liu, Dimitris Papanikolaou for useful comments. We are grateful to Tobin Center for Economic Policy at Yale for funding the data acquisition for this project. Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this information product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2012 (CBDRB-FY22-P2012-R10065).

1 Introduction

We build a model that accounts for a variety of aggregate and cross-sectional asset pricing facts and is jointly consistent with predictions of modern macroeconomic models focused on firm behavior. Specifically, we combine the main features of production-based asset pricing models (e.g., Jermann, 1998; Zhang, 2005; Bai, Hou, Kung, Li and Zhang, 2019; Chen, 2017) with a state-of-the-art heterogeneous firm model with investment frictions and aggregate uncertainty in general equilibrium (Thomas, 2002; Khan and Thomas, 2008). We argue that this combination is important as such macroeconomic models have not been designed to match the asset pricing facts while production-based asset pricing models have not focused on delivering the detailed cross-sectional and aggregate firm-level implications that have been at the center of this strand of macroeconomic literature.

The two sides of our model are as follows. On the macroeconomic side, we build a production economy in the spirit of Khan and Thomas (2008) that features both convex and non-convex capital adjustment costs, thereby generating a lumpy (Cooper and Haltiwanger, 2006) and right-skewed (Bai, Li, Xue and Zhang, 2022) investment rate distribution. The model is set in general equilibrium which imposes a higher standard of internal consistency relative to partial equilibrium frameworks. One important new feature of our model is that a small share of firms every period experiences a large negative idiosyncratic productivity shock—a firm-level microeconomic disaster, or a jump. Several important recent papers in asset pricing literature argue that micro-level jumps play a prominent role. Schmidt (2022) develops a model with microeconomic disasters on the worker side which matches the level and dynamics of the equity premium; we, in turn, consider such shocks on the firm side. McQuade (2018) introduces firm-level jumps to account for empirical default frequencies and credit spreads. Oh and Wachter (2022) argue that fat-tailed idiosyncratic shocks are needed to generate the skewed cross-section of stock returns. Recent macroeconomic literature that analyzes detailed administrative data also documents deviations of productivity and employment changes from normality (Kehrig, 2015; Salgado, Guvenen and Bloom, 2020). In particular, shocks are heavy-tailed and exhibit procyclical skewness; that is, in recessions, large negative shocks become more likely than large positive ones (Dew-Becker, 2022). One natural way to account for such features of the data is to introduce jumps with a time-varying size (Cont and Tankov, 2003; Tsai and Wachter, 2015). We establish detailed characteristics of firm-level microeconomic disasters using high-quality microdata from U.S. Census Bureau. These data cover a universe of U.S. businesses from 1976 and thus provide comprehensive scope and time span that allows us to precisely parameterize these firm-level rare events and their evolution in the model, which are difficult to estimate with less granular data.

On the asset pricing side, our model is most closely related to Jermann (1998) and Chen (2017) in the aggregate, and Zhang (2005); Chen (2018); Bai, Hou, Kung, Li and Zhang (2019) and Ai, Li and Tong (2021) in terms of cross-sectional asset pricing implications. As McQuade (2018) and Schmidt (2022), we emphasize the role of microeconomic disasters. We show that our model accounts for important asset pricing moments, both aggregate and cross-sectional. For instance, the model produces a large and volatile equity premium, a small and stable risk-free rate and a time-varying risk-premium. We highlight the role that microeconomic disasters play in accounting for these and other asset pricing implications.

One contribution of our model is that it jointly delivers firm-level empirical facts emphasized by macroeconomic literature on heterogeneous firms over the business cycle, as well as proper cross-sectional and aggregate asset pricing implications emphasized by the production-based asset pricing finance literature. First, both convex and non-convex capital adjustment frictions allow the model to generate a lumpy investment rate distribution; these adjustment frictions are also important both for the aggregate and cross-sectional behavior of asset prices. Second, jumps with time-varying sizes play two key roles. On one hand, they yield heavy tails of employment changes which we document in the data. On the other hand, microeconomic disasters increase volatility of aggregate investment and dividend rates of productive firms by over 20 percent while having virtually no impact on the least productive ones; as a result, jumps represent an important determinant of value and investment premiums. Third, the comprehensiveness of the U.S. Census data allows us to precisely parameterize the firm-level shock process, in particular its persistence, which is central to cross-sectional asset pricing implications. Finally, the general equilibrium setting of our model ties the time-series evolution of the marginal utility with an endogenous consumption decision of the household, thereby making the stochastic discount factor internally consistent (Kogan and Papanikolaou, 2012).

In the second part of the paper, we apply our model to quantitatively study macroeconomic and asset pricing implications of supply chain disruptions and disasters.[1] Global pressures on supply chains have increased substantially and are currently at the historically high levels, as is reflected by virtually all aggregate supply chain indices (e.g., Benigno, di Giovanni, Groen and Noble, 2022); this is a major concern of policymakers.[2] One contribution of our paper is to provide a cross-sectional and aggregate analysis of supply chain disruptions and disasters using a novel, large-scale data on the universe of seaborne U.S. import that cover nearly 200 million transactions and span the time period starting from 2007. An important advantage of this dataset is the exceptionally detailed information accompanying each shipment; three pieces of information are particularly important. First, we use the exact identities of consignees (importers) and shippers (suppliers) to measure supply chain disruptions and disasters at the individual consignee level. Second, we associate each shipment with the ultimate parent company, and merge these parent-level data with Compustat. We find that supply chain disruptions are associated with a pronounced decline in sales growth, and that the share of firms that experience supply chain disruptions is sizable in the bottom part of the sales growth distribution. Third, we use the detailed data on the exact volume of each shipment (in twenty-foot equivalent units, TEUs) to characterize not only the occurrence but also the size distribution of supply chain disruptions. In particular, we are able to measure the prevalence and evolution of both supply chain disruptions and supply chain disasters. We document that, while supply chain disruptions have indeed become more common in the last 3-4 years, the probability of very large disruptions increased

[1]In an important early paper Cohen and Frazzini (2008) investigate how asset prices of economically connected firms co-move through the supplier-customer relationship. In this paper, we focus on how returns of firms-customers respond to supply shocks. In a more recent study, Jain and Wu (2020) demonstrate that global sourcing strategies can predict future stock returns.

[2]See, for example, the recent Biden-Harris plan to secure critical supply chains (White House, 2022).

even more and nearly doubled over the same time period.

We then quantitatively evaluate the effects of these recent changes that we empirically document. In the aggregate, the effect of higher supply chain disasters is naturally muted as they account for only a small share of all firm-level disasters; we find that the equity premium increases by 0.2pp. However, this effect is highly non-monotonic in the cross-section; in particular, the expected return of high book-to-market firms increases by 0.5pp and of low investment firms by 0.3pp. At the same time, the impact on growth stocks and high investment firms is negligible. We further evaluate the performance of the model by empirically studying the impact of identified supply chain disruptions on realized stock returns and show that disruptions, especially large ones, reduce returns of value stocks more strongly than those of growth stocks. Similarly, identified disruptions reduce returns of low investment firms by more relative to high investment stocks.

2 Empirical Evidence On Employment Changes

In this section, we draw on the universe of U.S. firms to first show that the distribution of employment changes in the data exhibits heavy tails: The probability of large changes is much higher than what is implied by a Gaussian density. Furthermore, we demonstrate that larger shocks are more transient than smaller shocks; we use this insight to put discipline on the model developed in the next section.

2.1 Data

We use the Longitudinal Business Database (LBD) housed by the U.S. Census Bureau. The LBD is an administrative panel dataset that covers the universe of non-farm establishments in the U.S. private sector. The unit of observation is an establishment, which is defined as a single physical location where business is conducted. We perform analysis at the firm-level, which requires rolling up plant-level data to the company-level. See Appendix A.1 for details.

Table 1: Concentration Statistics of Employment Growth

	$P(\lvert\Delta \log n\rvert \in S)$				
$S:$	≤ 0.05	≤ 0.10	≤ 0.20	$\geq 2\sigma$ (≈ 0.8)	$\geq 3\sigma$ (≈ 1.2)
Data	0.444	0.492	0.604	0.059	0.021
$\mathcal{N}(0, 0.41)$	0.097	0.193	0.374	0.046	0.003
Ratio	4.577	2.549	1.615	1.283	7.000

Notes: The empirical distribution used in these calculations is based on U.S. Census LBD for years 2005-2006. Establishment-level data has been rolled up to the firm-level; see Appendix A.1 for details.

2.2 Heavy-Tailed Distribution of Employment Changes

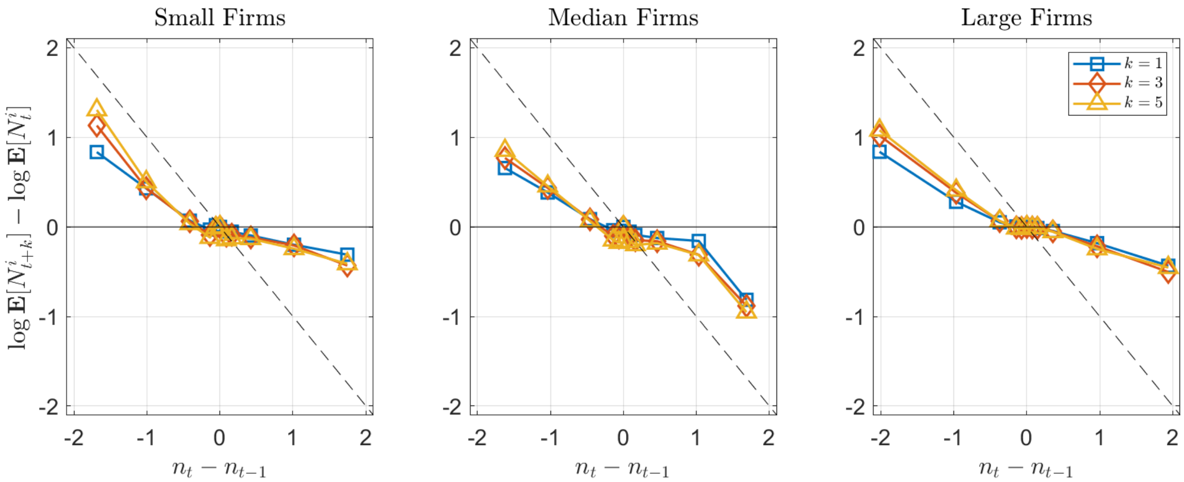
In the data, the distribution of employment changes exhibits heavy tails. To illustrate this point, we calculate concentration measures for employment changes of various sizes (see Table 1). In the data, about 44 percent of firms experience an employment change of less than 5 percent, whereas if shocks were drawn from a normal distribution with the same standard deviation as in the data, only about 10 percent of firms would experience such changes.

Importantly, extreme events are more likely in the data: A typical firm experiences a change larger than three standard deviations (120 log points) with a probability of 2.1 percent per annum, whereas this probability is one-seventh that size under a normal distribution. Overall, the table suggests that modeling idiosyncratic shocks as random draws from a Gaussian density—a standard assumption in numerous macro-finance models—will fail to account for rare and large shocks we observe in the data.

2.3 Mean-Reversion of Employment Changes

We now adopt a nonparametric strategy to characterize the nonlinear mean-reversion of employment shocks of various sizes. We do so by documenting the impulse response functions of employment changes of different sizes and signs for firms of different sizes. In particular, we group firms by their employment growth between $t-1$ and t, and their size, and then follow their employment over the next 5 years; our approach follows Guvenen, Karahan, Ozkan and Song (forthcoming) who studied labor income shocks. We compute employment growth

Figure 1: Empirical Impulse Response Functions



Notes: Figure 1 consists of three panels. The graphs demonstrate the mean reversion of employment changes of various size for small (recent size $\in (P5, P10]$), median (recent size $\in (P45, P55]$) and large (recent size $\in (P90, P95]$) firms. The average mean reversion varies across the RS groups because of different employment histories. Therefore, we normalize employment changes on both the x- and y-axes such that their values at the median 6th group of $n_t - n_{t-1}$ cross at zero. For additional details, see Section 2.3. Datasource: Longitudinal Business Database.

rates between $t-1$ and t as the log difference, $n^i_t - n^i_{t-1}$, where $n^i_t = \tilde{n}^i_t - d_{t,j(i,t),a(i,t)}$ denotes the log employment ($\tilde{n}^i_t$) of firm i in year t net of age $a(i,t)$, industry $j(i,t)$ (at NAICS 2-digit level) and year t fixed effects. We obtain n^i_t by regressing $\tilde{n}^i_t$ on a full set of age dummies separately for each industry-year. The average size of firm i between years $t-5$ and $t-1$ is $RS^i_t = \frac{1}{5}\sum_{p=1}^{5} \widetilde{N}^i_{t-p}$, where $\widetilde{N}^i_t$ denotes employment of firm i in year t. We keep only those firm-year observations for which we have at least 3 non-missing employment observations in the preceding 5 years. We control for age, industry and year effects by regressing average employment on age dummies for each industry-year, and call the residuals as *recent size* (RS).

We rank and group individual firms into the following 20 RS percentiles: 15, . . . , 96100. Next, within each RS group, we group firms by the size of their log employment change between $t-1$ and t into the following 11 categories: $\Delta \log n \in (-\infty, -3\sigma)$, $[-3\sigma, -2\sigma)$, $[-2\sigma, -\sigma)$, $[-\sigma, -0.1)$, $[-0.1, -0.05)$, $[-0.05, 0.05)$, and so on.[3] This way we ensure that all firms within a group have similar sizes up to $t-1$, and experience a similar change in

[3]In our application, we use the standard deviation of log employment changes based on years 1976-2016 in the LBD, $\sigma = 0.41$.

employment from $t-1$ to t. For each such group of firms, we then compute the log change of their average employment from t to $t+k$, $\log \mathbb{E}[N^i_{t+k}] - \log \mathbb{E}[N^i_t]$, where N^i_t is employment net of age, industry and time effects. Rather than taking the average of log employment changes, this approach allows us to keep the composition of firms constant for each horizon k.

Figure 1 shows empirical impulse-response functions (IRFs) for small (RS $\in (P5, P10]$), median (RS $\in (P45, P55]$) and large (RS $\in (P90, P95]$) firms. Values on the horizontal axis measure the size of log employment changes from year $t-1$ to t, while values on the vertical axis represent the log change of average employment at horizons of 1, 3, and 5 years. Thus, the closer the IRF is to the dashed diagonal line, the more transient the shock is. And, conversely, the closer IRF is to the horizontal solid line, the more persistent the employment change is.

There are several important observations. First, across the entire firm-size distribution, small shocks are more persistent than large shocks. In particular, large negative shocks tend to be more transient for small firms (and mean-revert by about two-thirds over 5 years), whereas these shocks are somewhat more persistent for median and large firms. At the same time, smaller shocks do not mean-revert nearly as fast across all three size groups.

Moreover, the sign of employment changes matters for the nature of mean-reversion; large positive shocks appear to be more persistent than large negative shocks, especially for small and large firms. Interestingly, large positive shocks for large firms are almost as persistent as they are for small firms. This feature of the firm-level data is at stark contrast with labor income dynamics; Guvenen, Karahan, Ozkan and Song (forthcoming) find that the speed of mean reversion of large positive shocks increases in worker's income, while our findings suggest it is not monotonic in firm size. Finally, we note that large firms experience larger tail shocks, since the average employment change in the first and last groups are more extreme for large firms relative to small and median ones.

In summary, this section demonstrates a tremendous heterogeneity in mean-reversion of employment changes depending both on the size of the firm and the size of the shock itself. Critically, the data reveal that large shocks are more transient than small employment changes; we later use our quantitative model to show that this has important cross-sectional implications (Schmidt, 2022).

3 Model

We build a model of industry dynamics with heterogeneous firms in the spirit of Khan and Thomas (2008) and Bachmann, Caballero and Engel (2013) on the macro side and Jermann (1998) and Chen (2017) on the asset pricing side.[4] Time in the model is discrete and the horizon is infinite. The economy is populated by heterogeneous firms and a representative household. There is a single final good produced by firms which can be either consumed or invested. Households own shares in firms, supply labor, and consume the final good.

3.1 Environment

Technology Every firm i has access to a Cobb-Douglas production technology with decreasing returns to scale:

$$y(X_t^Z, z_{it}, n_{it}, k_{it}) = e^{X_t^Z} e^{z_{it}} k_{it}^{\alpha} n_{it}^{\nu}$$

with $\alpha, \nu > 0$ and $\alpha + \nu < 1$. Every firm produces a homogeneous output y_{it} by combining capital k_{it} and labor n_{it} with corresponding shares α and ν. The production function is scaled by an aggregate component X_t^Z and idiosyncratic component z_{it}. Aggregate productivity component X_t^Z affects all firms simultaneously; it follows an AR(1) process:

$$X_{t+1}^Z = \rho_Z X_t^Z + \varepsilon_{t+1}^Z, \qquad \varepsilon_{t+1}^Z \sim \mathcal{N}(0, \sigma_Z), \tag{1}$$

[4]Other related research includes studies of entry dynamics (e.g., Clementi, Khan, Palazzo and Thomas, 2015; Clementi and Palazzo, 2016; Smirnyagin, 2022) and financial frictions (Khan and Thomas, 2013; Khan, Senga and Thomas, 2014).

where $\rho_Z \in (0,1)$. Idiosyncratic component z_{it} follows an AR(1) process with the persistence parameter $\rho_z \in (0,1)$:

$$z_{it+1} = \rho_z z_{it} + \chi(X_t^Z) J_{it} + \varepsilon_{t+1}^z, \tag{2}$$

$$\chi(X_t^Z) = -\rho_0 e^{-\rho_1 X_t^Z}. \tag{3}$$

A jump component J_{it} in Equation (2) is a Poisson random variable with arrival rate λ, and ε_{t+1}^z is drawn from the normal distribution with mean 0 and variance σ_z^2. A share λ of firms experiences a jump downward each period; the size of the jump $\chi(X_t^Z)$ is a function of the aggregate state X_t^Z. Assuming strictly positive parameters ρ_0 and ρ_1, this specification implies that jumps are non-positive and larger in worse aggregate times, i.e. for low values of X_t^Z. The timing is such that the size of the jump is known to firms at the beginning of period t.

Labor Labor market is frictionless with the wage rate W_t.

Investment Firms enter period t with some predetermined idiosyncratic level of capital k_{it}. The capital in period $t+1$ is determined by depreciation and investment made in period t. Capital depreciates at a rate δ. Investment is costly, and firms which would like to make an unconstrained choice of capital for period $t+1$ have to pay a cost $\eta \geq 0$ denominated in units of labor. Firms draw η from some distribution F^η independently across time and space.

Financing There is a representative household which owns all firms; the proceeds from production net of depreciation and investment are paid out to the household as dividends d_{it}. We assume no frictions on financial markets, and, thus, place no constraints on the value of d_{it}.

Households The economy is populated by a unit mass of identical households. Each household consumes, supplies labor, and saves into firms' shares. Investment in firms is a device households use in order to smooth consumption over time.

3.2 Firm Optimization

Beginning of the Period Let $\mathbf{S}$ denote the aggregate state that consists of the distribution of firms over the idiosyncratic states $\mu = \mu(k, z)$, as well as the value of an aggregate shock X_t^Z. The firm enters the period with some pre-determined level of capital k. Idiosyncratic productivity z is realized at the beginning of the period. Let $v(k, z; \mathbf{S})$ denote the value of the firm at the start of the period given the idiosyncratic state (k, z) and the aggregate state $\mathbf{S}$.

After the production stage takes place, firms learn the cost of capital adjustment $\eta \sim F^\eta$. Thus, the value of the firm at the start of the period can be written as:

$$v(k, z; \mathbf{S}) = \pi(k, z; \mathbf{S}) + \int \max\{v^{\text{adj}}(k, z; \mathbf{S}) - \eta W(\mathbf{S}), v^{\text{no adj}}(k, z; \mathbf{S})\} \mathrm{d}F^\eta, \tag{4}$$

where firm profits π are defined as:

$$\pi(k, z; \mathbf{S}) = \max_{n \geq 0} e^{X^Z} e^z k^\alpha n^\nu - W(\mathbf{S})n. \tag{5}$$

Objects v^{adj} and $v^{\text{no adj}}$ in (4) are values the firm attains in case of unconstrained and constrained capital choices, respectively.The profit maximization problem (5) is the static choice of the labor input.

We assume that the cost of a capital adjustment is distributed uniformly: $\eta \sim U[0, \bar{\eta}]$. The firm will choose to undertake an unconstrained investment conditional on the realization of the cost shock η if and only if

$$v^{\text{adj}}(k, z; \mathbf{S}) - W(\mathbf{S})\eta \geq v^{\text{no adj}}(k, z; \mathbf{S}).$$

For each firm indexed by its state $(k, z; \mathbf{S})$, there is a threshold value of $\eta^*(k, z; \mathbf{S})$ such that the firm always chooses to make an unconstrained investment if $\eta < \eta^*(k, z; \mathbf{S})$, and prefers to be constrained if $\eta \geq \eta^*(k, z; \mathbf{S})$. It follows that the threshold is given by

$$\eta^*(k, z; \mathbf{S}) = \frac{v^{\text{adj}}(k, z; \mathbf{S}) - v^{\text{no adj}}(k, z; \mathbf{S})}{W(\mathbf{S})}. \tag{6}$$

Provided that η has bounded support, we reformulate the definition of the threshold to force it to lie within the interval $[0, \bar{\eta}]$:

$$\widehat{\eta}(k, z; \mathbf{S}) = \min\{\bar{\eta}, \max\{0, \eta^*(k, z; \mathbf{S})\}\}. \tag{7}$$

We, therefore, can rewrite the value of a firm at the start of the period (4) as follows:

$$\begin{aligned} v(k, z; \mathbf{S}) = \pi(k, z; \mathbf{S}) + \left(\frac{\widehat{\eta}(k, z; \mathbf{S})}{\bar{\eta}}\right) \left[v^{\text{adj}}(k, z; \mathbf{S}) - W(\mathbf{S})\frac{\widehat{\eta}(k, z; \mathbf{S})}{2}\right] + \\ + \left(1 - \frac{\widehat{\eta}(k, z; \mathbf{S})}{\bar{\eta}}\right) v^{\text{no adj}}(k, z; \mathbf{S}). \end{aligned} \tag{8}$$

Value of Adjusting If the firm chooses to adjust (i.e., to make an unconstrained capital choice), then it solves the following programming problem

$$v^{\text{adj}}(k, z; \mathbf{S}) = \max_{k' \geq 0} -i - AC(k', k) + \mathbb{E}[M(\mathbf{S}, \mathbf{S}')v(k', z'; \mathbf{S}')], \tag{9}$$

$$k' = (1 - \delta)k + i, \tag{10}$$

$$AC(k', k) = \frac{\varphi}{2}\left(\frac{i}{k}\right)^2 k, \tag{11}$$

$$\mathbf{S}' \sim \mathbf{\Gamma}(\mathbf{S}'|\mathbf{S}), \tag{12}$$

where $\mathbf{\Gamma}$ is the firm's perceived law of motion of the aggregate state and $M(\mathbf{S}, \mathbf{S}')$ is a stochastic discount factor. Parameter φ governs the extent of quadratic adjustment costs $AC(\cdot)$ in the economy.

Value of Not Adjusting The value of not adjusting $v^{\text{no adj}}$ solves a similar to (9)-(12) programming problem with the only difference that the firm's investment rate is bounded by some small positive number b: $k' \in [(1-\delta-b)k, (1-\delta+b)k]$.

3.3 Household Optimization

The representative household maximizes the discounted stream of utilities subject to the budget constraint. We assume that labor is supplied inelastically, $\overline{N}=1$. The wealth is held in one-period firm shares, $\xi(k,z)$. The price of current shares is ω_0, and the purchase price of new shares is ω_1. The household's dynamic programming problem is then

$$H(\mathbf{S}) = \max_{c,\xi'} \left[U(c) + \beta \mathbb{E} H(\mathbf{S}')\right] \tag{13}$$

subject to

$$c + \int \omega_1(k', z'; \mathbf{S}) \mathrm{d}\xi' \leq W(\mathbf{S})\overline{N} + \int \omega_0(k, z; \mathbf{S}) \mathrm{d}\xi. \tag{14}$$

The right-hand side of (14) represents the resources available to the household; it consists of firm shares coming from the previous period, as well as labor income. Part of these resources is consumed, and the rest is reinvested into firm shares.

Utility We consider preferences with external habit formation of the following form:

$$U = \frac{(C_t - H_t)^{1-\sigma}}{1-\sigma}, \tag{15}$$

where H_t is a habit stock (Campbell and Cochrane, 1999). We define the habit stock H_t to capture the idea that utility over current consumption is judged relative to the past consumption. Specifically, we first define the surplus consumption ratio as

$$S_t := \frac{C_t - H_t}{C_t}, \tag{16}$$

and then define the law of motion for S_t:

$$S_{t+1} = \bar{S}^{1-\rho_H} S_t^{\rho_H} \left(\frac{C_{t+1}}{C_t}\right)^{\lambda_H}. \tag{17}$$

Let $C(\mathbf{S})$ be the household's consumption policy function. Also, let $\Xi(k', z'; \mathbf{S})$ be a number of shares purchased in firms which start next period with capital k' and idiosyncratic productivity component z'. The detailed definition of equilibrium is relegated to Appendix B.1.

Solution Method It is challenging to solve the model with heterogeneous firms and aggregate uncertainty, since the entire distribution of firms across idiosyncratic states becomes a part of a state vector. One broadly applied method to deal with this infinitely dimensional object is to assume that agents only use a finite number of moments of the cross-sectional distribution to form expectations about the future (Krusell and Smith, 1998). The main advantage of this method is the accuracy of decision rules with respect to aggregate shocks. This, however, comes at a cost; the set of moments used in forecasting equations is typically arbitrary, and the entire method is generally slow.

We take a different approach, and solve the model in two steps. First, we use global methods to compute the steady-state of the model economy. Specifically, we apply collocation methods to solve the firm's functional equations. Subsequently, we perform a second-order perturbation of the model around the steady-state with respect to an aggregate productivity shock, preserving the full non-linearity of firm-level decision rules with respect to idiosyncratic states (Reiter, 2009; McKay and Reis, 2016; Winberry, 2018). Further computational details are in Appendix B.

There are two important aggregate limiting cases of our model: the representative firm frameworks of Jermann (1998) and Chen (2017).[5] As an additional accuracy check of our algorithm, we turned off cross-sectional heterogeneity in our model by setting both ρ_z and σ_z to 10^{-4} (along with dropping non-convex capital adjustment costs), and reproduced key business cycle statistics and asset pricing moments reported in aforementioned studies.

[5] Another limiting case that we considered is an important paper by Chen (2018) who studied a heterogeneous firm model in general equilibrium with only convex adjustment costs.

Table 2: Parameter Values

Parameter	Description	Value	Target/Source	Data	Model
β	Discount factor	0.989	90-day Treasury-bill return	0.24	0.20
α	Capital share	0.210			
ν	Labor share	0.640			
σ	Utility curvature	2	Campbell and Cochrane (1999)		
δ	Depreciation rate	0.025	$\mathbb{E}\left[\frac{i}{k}\right]$	0.10	0.10
ρ_z	Persistence of idiosyncratic AR(1)	0.880	Mean-reversion of emp. changes		
σ_ε	Std of idiosyncratic AR(1)	0.038	$\mathbb{E}[P9010(\Delta \log n)]$	0.56	0.62
b	Adj. region	0	–		
$\bar{\eta}$	Upper bound non-convex	0.012	$P\left[\left\lvert\frac{i}{k}\right\rvert > 0.2\right]$	0.14	0.17
φ	Quadratic adj. cost	0.450	$\sigma\left[\frac{i}{k}\right]$	0.16	0.12
$\bar{S}$	Steady state surplus consumption	0.100	Mean Sharpe ratio	0.44	0.37
ρ_H	Habit persistence	0.980	Benchmark value		
λ_H	Habit sensitivity	$\frac{1}{\bar{S}} - 1$	Chen (2017)		
ρ_Z	Persistence of aggregate TFP	0.980	Benchmark value		
σ_Z	Std of aggregate TFP	0.014	$\sigma(Y)$	1.78	1.82
ρ_0	Size of jump	0.303	$\mathbb{E}[P5010(\Delta \log n)]$	0.26	0.31
ρ_1	Sensitivity of jump	4.050	$\sigma[P5010(\Delta \log n)]$	0.03	0.03
λ	Jump intensity	0.011	$P[\Delta \log n \leq -3\sigma]$	0.01	0.01

4 Parameterization and Model Fit

We set the model period to be one quarter. The time preference parameter β is chosen to fit the mean return on 90-days Treasury bills. We set the labor share $\nu = 0.64$ and choose the capital share α so that the total returns to scale are 85 percent. Utility curvature is equal to 2 (Campbell and Cochrane, 1999).

Depreciation rate is $\delta = 0.025$ such that the mean annual investment rate is 10 percent. The persistence ρ_z for the idiosyncratic productivity process is set such that large negative employment changes ($\Delta \log n_t^i < \mu - 3\sigma$) recover by one-half over the course of 5 years among firms with the median recent size, in line with empirical evidence reported in Section 2. Idiosyncratic volatility $\sigma_z = 0.038$ is set to match the time-series average of the interdecile range of employment changes in the data. The upper bound of non-convex capital adjustment costs $\bar{\eta} = 0.012$ is set to match the probability of investment spikes, and the quadratic adjustment costs parameter $\varphi = 0.45$ is chosen to generate the observed dispersion of investment rates (investment moments are from Zwick and Mahon, 2017).[6] We set $b = 0$, i.e. in case of a constrained investment decision firms let current capital depreciate. We set

[6] An investment spike is a situation when the investment rate exceeds 20 percent in absolute value.

ρ_Z, the persistence of aggregate TFP, to a benchmark value of 0.98. The standard deviation of innovations to aggregate TFP $\sigma_Z = 0.014$ is set to match the volatility of GDP.

The size of the jump ρ_0 governs the length of the left tail of log employment changes, we set $\rho_0 = 0.303$ to capture the average value $\mathbb{E}[P5010(\Delta \log n)] = 0.26$. The sensitivity parameter ρ_1 is set to match a time-varying left tail of log employment changes; thus, volatility of $P5010(\Delta \log n)$ is a natural target to identify this parameter.[7] Finally, the Poisson arrival rate $\lambda = 0.011$ is chosen such that the probability of large negative events ($\Delta \log n \leq \mu - 3\sigma$) aligns with the data.

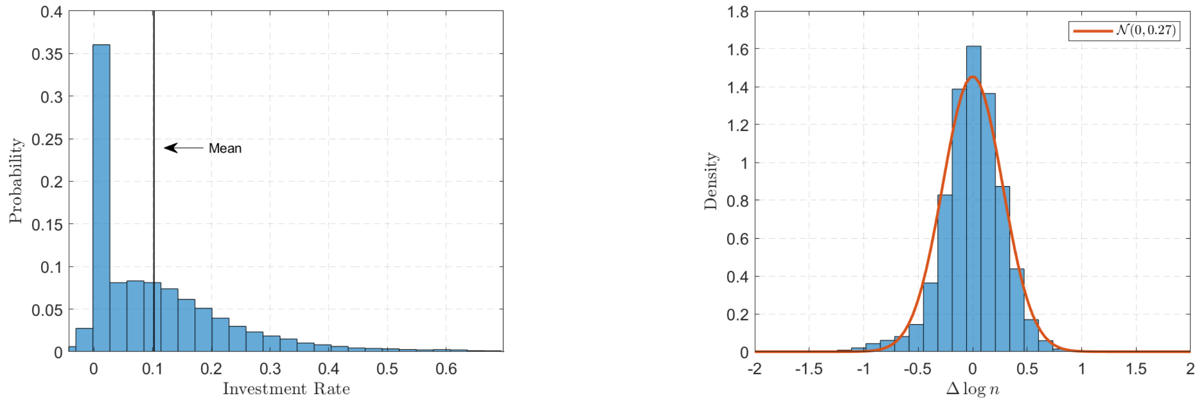
Typically, it is assumed that λ_H is a decreasing function of surplus consumption; this generates a countercyclical volatility of marginal utility and leads to a time-varying risk premium. However, we assume that the sensitivity of habit is constant over the business cycle, and is equal to $\lambda_H = \frac{1}{\bar{S}} - 1$. It turns out that production economies accompanied by precautionary motives endogenously generate countercyclical consumption volatility, thereby accounting for the smooth risk-free rate and high and volatile equity premium (Chen, 2017). We set $\bar{S} = 0.10$ to match a mean (annual) Sharpe ratio of excess returns of 0.44. Persistence of habit ρ_H is set to the benchmark value of 0.98; we present sensitivity analysis of this choice in Section 5.4. Table 2 summarizes the parameterization of the model.

5 Macroeconomic and Asset Pricing Implications

This section discusses macroeconomic and asset pricing implications of the model developed in the previous section. We first demonstrate in Section 5.1 that the model generates a lumpy investment rate distribution and a heavy-tailed distribution of employment changes, and discuss the role of microeconomic disasters in accounting for these features. We then show in Section 5.2 that the model successfully accounts both for aggregate asset pricing and key business cycle statistics. Section 5.3 demonstrates that the time-varying risk premium in the model gives rise to predictable returns. Furthermore, Sections 5.4 and 5.5 first discuss

[7] Both the length and volatility of the left tail of log employment changes are sourced from Salgado, Guvenen and Bloom (2020).

Figure 2: Distributions of Investment Rates and Employment Changes in Steady State



(A) Distribution of investment rates (B) Distribution of employment changes

Notes: Figure 2 consists of two panels. Panel (A) plots the p.d.f. of investment rates in the steady state of the model. The vertical black line marks the mean investment rate in the simulated panel of firms. Panel (B) plots the distribution of employment log changes, $\Delta \log n$. The red line is the normal density with mean 0 and the same standard deviation as the simulated data.

the sensitivity of our results with respect to key structural parameters, and explain how microeconomic disasters generate high equity premium. We then study implications of the model for the cross-section of stock returns by showing that the model generates both the value and investment premiums (Sections 5.6 and 5.7). Finally, we demonstrate that the degree of mean-reversion of jump shocks is much more important for the cross-section of stock returns as compared with the persistence of small shocks (Section 5.8).

5.1 Cross-sectional Distributions

Figure 2 displays the model-generated distributions of investment rates (panel (A)) and employment log changes (panel (B)). Due to the fixed cost of capital adjustments, there is a considerable mass of observations with close-to-zero investment along with a substantial mass of observations with large positive investment spikes. It is worth noting that asset pricing literature made some progress with various types of quadratic costs (e.g., Zhang, 2005; Chen, 2018; Bai, Hou, Kung, Li and Zhang, 2019); however, it is challenging to capture the lumpy nature of investment without a non-convex component of capital adjustment costs.

Table 3: Aggregate Asset Pricing and Business Cycle Moments

Moment	Data	Model
$\mathbb{E}[r^f]$	0.89	0.79
$\mathbb{E}[r^e - r^f]$	6.36	6.56
$\sigma[r^f]$	1.82	2.46
$\sigma[r^e - r^f]$	16.52	18.50
$AC_1[r^f]$	0.84	0.99
$AC_1[r^e - r^f]$	0.08	0.00
$\sigma(Y)$	1.78	1.81
$\rho(C, Y)$	0.91	0.99
$\rho(I, Y)$	0.87	0.95
$\sigma(C)/\sigma(Y)$	0.82	0.52
$\sigma(I)/\sigma(Y)$	4.64	4.29

Notes: Table 3 reports asset pricing and business cycle statistics in the data and model. The symbols have the following meaning: r^f, risk-free rate, r^e, return to equity, Y, output, C, consumption, I, investment, $\sigma(\cdot)$, standard deviation, $AC_1(\cdot)$, autocorrelation, $\rho(\cdot)$, correlation. Only levels of macro aggregates (C, Y, and I) were log-differenced and HP-filtered with the smoothing parameter of 1600. Business cycle statistics are quarterly and asset return moments are annualized and reported in percentage terms. Model moments are the mean across 100 simulations of 500 quarters. We burn 200 first periods to reduce the impact of initial conditions.

Panel (B) demonstrates a left-skewed and heavy-tailed distribution of employment log changes; due to the presence of rare microeconomic disasters, the left tail is thicker as compared with normal density. In particular, the share of observations further than -3σ from the mean is about 9 times bigger relative to normal distribution; this accords well with empirical evidence reported in Section 2.

Table D18 in Appendix assesses the role of microeconomic disasters for cross-sectional distributions of investment rates and employment changes. We find that the distribution of investment rates is to a large extent invariant to microeconomic disasters; this is not surprising given that the model features both convex and non-convex capital adjustment costs which force capital to adjust slowly. However, the model features a frictionless labor market; thus, labor is more fluid than capital, and we see a significant impact of microeconomic disasters on the distribution of employment changes. Specifically, we find that jumps both increase the dispersion of the distribution and raise the share of firms that experience very large changes. Therefore, jumps play a key role in accounting for heavy tails of employment shocks observed in the data.

5.2 Aggregate Implications

The model matches important asset pricing and business cycle moments (Table 3). In particular, the model is capable of picking up aggregate asset pricing moments; the risk-free rate is small and stable, and the equity premium is large and volatile.[8] While the latter typically arises in habit models (e.g. Jermann, 1998; Campbell and Cochrane, 1999), the smoothness of the risk-free rate is achieved due to the countercyclical consumption volatility that counteracts low intertemporal elasticity of substitution (Chen, 2017). Specifically, the IES in external habit models is $\frac{\bar{S}}{\sigma} = 0.05$; this incentivizes the household to borrow from the future during downturns by selling the risk-free asset, thereby pushing up its return. On the other hand, an increase in consumption volatility in recessions activates the precautionary savings motive; this stimulates savings and, as a result, stabilizes the dynamics of the risk-free rate. The model also fits other time-series properties of asset prices: The risk-free rate is highly persistent, while the excess returns are nearly a random walk.

Furthermore, the model matches standard business cycle statistics. Investment is more volatile than output and consumption is less volatile than output in both the model and the data. All macroeconomic aggregates are highly correlated with each other since there is a single aggregate shock. Provided that jumps are idiosyncratic and rare, the quantitative impact of microeconomic disasters on aggregate business cycle dynamics is limited (see Table D19 in Appendix). Nevertheless, jumps have important quantitative implications in the cross-section. To demonstrate this, we sort firms into quintiles with respect to idiosyncratic productivity and re-sort them every four quarters. Table 4 shows that microeconomic disasters have a sizable impact on aggregate investment and dividend rates in the cross-section. Specifically, we find that, in the absence of jumps, least productive firms have lower investment and, accordingly, higher dividend rates. At the same time, the time-series volatility of both rates is monotonically increasing in productivity; the dividend rate of the most productive firms is about 10 percent more volatile relative to unproductive firms. Incorporating

[8] We compute the expected (gross) risk-free rate as $\mathbb{E}[R_t^f] = \mathbb{E}\left[\frac{1}{\mathbb{E}_t M(\mathbf{S},\mathbf{S}')}\right]$, and the equity return as $R^e(\mathbf{S}'|\mathbf{S}) = \frac{\int v(k',z';\mathbf{S}')\mathrm{d}\mu'}{\int [v(k,z;\mathbf{S}) - d(k,z;\mathbf{S})]\mathrm{d}\mu}$, where $d(k,z;\mathbf{S}) = y(k,z;\mathbf{S}) - W(\mathbf{S})n(k,z;\mathbf{S}) - i(k,z;\mathbf{S}) - AC(k,k')$.

Table 4: Aggregate Investment and Dividend Rates by Productivity Quintile

	$\lambda = 0$				$\lambda = 0.011$			
Group	$\mathbb{E}\left[\frac{I}{K}\right]$	$\sigma\left[\frac{I}{K}\right]$	$\mathbb{E}\left[\frac{D}{K}\right]$	$\sigma\left[\frac{D}{K}\right]$	$\mathbb{E}\left[\frac{I}{K}\right]$	$\sigma\left[\frac{I}{K}\right]$	$\mathbb{E}\left[\frac{D}{K}\right]$	$\sigma\left[\frac{D}{K}\right]$
Low	1.1	1.5	4.1	2.1	0.8	1.5	4.1	2.1
2	2.0	1.7	3.9	2.3	1.8	2.0	4.2	2.8
3	2.5	1.7	3.7	2.3	2.5	2.0	3.9	2.8
4	2.9	1.9	3.6	2.3	3.1	2.2	3.8	2.8
High	3.6	2.3	3.6	2.3	3.9	2.5	3.6	2.8

Notes: Table 4 reports the mean aggregate investment and dividend rates by productivity quintile for two versions of the model: with jumps ($\lambda = 0.011$) and without them ($\lambda = 0$). Firms are sorted into quintiles based on idiosyncratic productivity and are re-sorted every 4 quarters. Model moments are averages across 100 simulations with 500 quarters each; 200 first quarters are discarded to reduce the impact of initial conditions. Figures are quarterly and in percent.

jumps ($\lambda = 0.011$) makes the difference between productive and unproductive firms more striking. In particular, the standard deviation of the dividend rate in the top quintile is about 30 percent higher than that in the bottom quintile. The entire difference is accounted for by the higher volatility of more productive firms; Section 5.6 argues that this has important implications for the cross-section of stock returns.

5.3 Predictability of Dividend Growth and Excess Returns

Table 5 reports regression results of excess equity returns and future dividend growth on price dividend ratio. The table shows that the model matches key empirical facts about the time-varying risk premium, since the price dividend ratio has a strong predictive power for future excess returns.

As per future dividend growth, slope coefficients in the model simulated data have the right sign and are slightly higher than those in the data; however, the current price dividend ratio has a strong predictive power for future dividend growth. The reason why our model exhibits high predictability of the dividend growth emerges due to the (relatively) low variance of innovations to idiosyncratic productivity σ_z. We choose this parameter to capture the interdecile range of log employment changes; the low value of σ_z which the model needs to fit that moment results in a relatively low noise in future stream of dividends, making its

TABLE 5: PREDICTABILITY OF EXCESS RETURNS AND DIVIDEND GROWTH

		Dependent Variable							
		$\sum_{j=1}^{L}(r_{m,t+j} - r_{f,t+j})$				$\sum_{j=1}^{L} \Delta d_{m,t+j}$			
			Model				Model		
	L(years)	Data	Mean	P5	P95	Data	Mean	P5	P95
$\widehat{\beta}$	1	-0.12	-0.08	-0.18	-0.02	0.00	0.03	0.01	0.06
	3	-0.27	-0.23	-0.45	-0.08	0.01	0.10	0.03	0.19
	5	-0.42	-0.35	-0.71	-0.12	0.04	0.17	0.06	0.33
t-stat	1	-2.63	-1.85	-3.35	-0.47	0.11	2.22	0.68	3.29
	3	-3.19	-3.42	-7.21	-0.92	0.19	4.40	2.15	6.27
	5	-3.37	-4.49	-9.57	-0.85	0.48	6.20	3.49	9.20
R^2	1	0.09	0.07	0.00	0.16	0.00	0.08	0.01	0.15
	3	0.19	0.18	0.01	0.47	0.00	0.25	0.07	0.40
	5	0.26	0.26	0.01	0.62	0.01	0.39	0.18	0.60

Notes: Table 5 reports the OLS estimates of regressions of the form $Y = \alpha + \beta(p_{m,t} - d_{m,t}) + \varepsilon_t$, where the left-hand side variable Y is either the dividend growth, $\sum_{j=1}^{L} \Delta d_{m,t+j}$, or the excess return, $\sum_{j=1}^{L}(r_{m,t+j} - r_{f,t+j})$. The symbols have the following meaning: $d_{m,t}$, the logarithm of value-weighted dividend, $p_{m,t}$, the logarithm of average value, $r_{m,t}$ is the log return weighted by value, $r_{f,t}$, the risk-free rate. Data moments are from Beeler and Campbell (2012). Model moments are the mean across 100 simulations of 500 quarters. We burn 200 first periods to reduce the impact of initial conditions. t-stats are Newey-West with $2(L-1)$ lags. Figures are annual and real.

growth highly predictable. Other asset pricing studies with heterogeneous firms (e.g., Bai, Hou, Kung, Li and Zhang, 2019) use other moments to inform this model parameter and typically calibrate σ_z to a much higher value. We experimented with larger values of this parameter and found that predictability of the future dividend growth gets reduced (at a cost of a significantly poorer fit of other cross-sectional moments).

5.4 Sensitivity Analysis

In this subsection, we discuss how sensitive our results are with respect to several key structural parameters.

A higher persistence of idiosyncratic shocks ρ_z reduces volatility of individual and, as a consequence, aggregate investment ($\sigma(I)/\sigma(Y)$ declines); thus, aggregate dividends become more volatile and the equity premium rises.

Increasing λ, the probability of microdisasters, by 2pp per quarter—from 0 to 0.02—

Table 6: Sensitivity to Parameter Values

Parameter	ρ_z		λ		ρ_1	
Value	L(0.850)	H(0.920)	L(0.000)	H(0.020)	L(1.000)	H(10.000)
$\mathbb{E}[r^f]$	1.00	0.96	1.24	0.28	1.00	0.24
$\mathbb{E}[r^e - r^f]$	5.08	7.72	4.96	8.28	6.24	7.20
$\sigma(r^f)$	4.40	2.32	2.28	2.54	2.52	2.64
$\sigma(r^e - r^f)$	22.36	15.24	15.62	18.24	18.08	19.24
$\sigma(C)/\sigma(Y)$	0.63	0.50	0.48	0.54	0.50	0.54
$\sigma(I)/\sigma(Y)$	5.19	4.52	4.36	4.13	4.37	4.10
Parameter	ρ_0		ρ_H		ρ_Z	
Value	L(0.100)	H(0.500)	L(0.970)	H(0.990)	L(0.970)	H(0.990)
$\mathbb{E}[r^f]$	1.16	-0.24	1.64	-0.72	1.96	-1.24
$\mathbb{E}[r^e - r^f]$	4.84	6.48	6.00	7.04	5.48	7.96
$\sigma(r^f)$	2.76	2.22	2.54	2.42	2.30	2.68
$\sigma(r^e - r^f)$	15.34	14.28	17.42	19.06	15.92	21.26
$\sigma(C)/\sigma(Y)$	0.51	0.57	0.47	0.59	0.44	0.62
$\sigma(I)/\sigma(Y)$	4.56	3.85	4.64	3.75	4.74	3.60

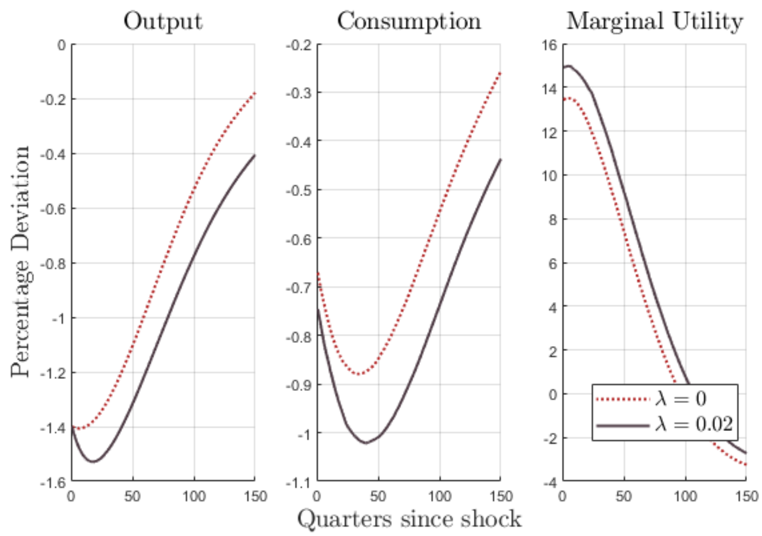
Notes: Table 6 reports the mean and standard deviation of the risk-free rate (r^f) and the equity premium ($r^e - r^f$), as well as the relative (to output, Y) volatilities of consumption C and investment I. Macro aggregates (C, Y, and I) were log-differenced and HP-filtered with the smoothing parameter of 1600. For each parameter considered, "L($\cdot$)" denotes the lower value, and "H($\cdot$)"—the higher value. Asset return moments are annualized and reported in percentage terms.

decreases the risk-free rate by 1pp and raises the equity premium by more than 3 percentage points per annum. As the odds of large negative events become higher (we show this more formally in Section 5.5), equity becomes riskier, and investors choose to save in a risk-free asset. This drives up its price and, thus, pushes down average returns. Qualitatively similar effects emerge in case of an increase in the size of the jump ρ_0 and the elasticity of the jump with respect to aggregate TFP, ρ_1.

The persistence of habit ρ_H directly governs the speed with which surplus consumption converges to the steady-state in the aftermath of an aggregate economic shock. Higher rate of mean-reversion of external habit increases time-series fluctuations in the marginal utility, thereby making firms riskier. Thus, the household prefers to save in a risk-free asset, leading to a lower risk-free return.

Finally, the effect of aggregate persistence ρ_Z is qualitatively similar to that of idiosyncratic ρ_z; investment becomes less volatile and the market premium rises. However, the

Figure 3: Impulse-Response Functions in Models with and without Microeconomic Disasters



Notes: Figure 3 plots impulse-response functions to a one standard deviation negative innovation to aggregate TFP. Model with microdisasters ($\lambda = 0.02$) is solid black, model without disasters ($\lambda = 0$) is dotted red.

impact of ρ_Z on the risk-free rate is quantitatively much stronger.

5.5 Microdisasters and Equity Premium

We have shown in Section 5.4 that a modest increase in the probability of a downward jump by 2pp raises equity premium by more than 3pp per annum. Figure 3 plots impulse-response functions of aggregate output, consumption, and marginal utility to a one standard deviation negative innovation to aggregate TFP.

Aggregate output falls by the same percentage upon impact in both models, since the effect of jumps manifests itself in the productivity only starting from the next period. However, from the next period onward, the two economies diverge reflecting the persistent effect of microeconomic disasters. Provided that large negative events limit the production capacity of the economy, aggregate consumption declines stronger in the economy with $\lambda = 0.02$. As a result, the marginal utility becomes more countercyclical. This makes investors care more about fluctuations in the dividend stream, thereby driving up the premium (Jermann, 1998).

Table 7: Summary Statistics for 5 B/M Sorted Portfolios

	$\mathbb{E}[R_{port}]$			$\sigma[R_{port}]$		
		Model			Model	
Portfolio	Data	$\lambda = 0$	$\lambda = 0.011$	Data	$\lambda = 0$	$\lambda = 0.011$
Low	7.5	4.8	4.7	18.9	17.5	16.2
2	7.8	4.8	4.7	16.2	17.0	15.5
3	8.5	5.2	5.3	15.8	17.0	15.5
4	9.3	5.8	6.3	18.0	17.0	15.8
High	11.7	6.5	8.6	20.3	17.1	16.5

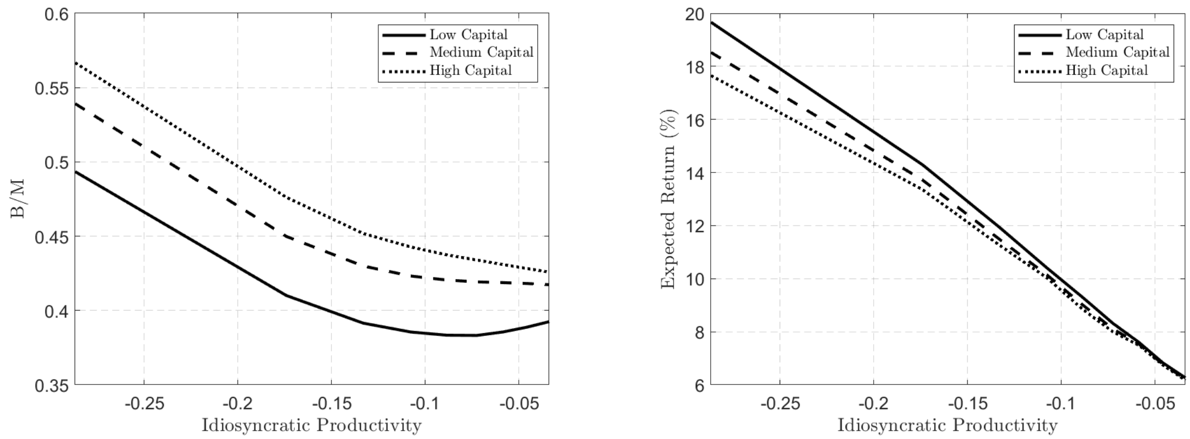
Notes: Table 7 reports the mean and the standard deviation of returns for 5 value-weighted portfolios using B/M. Returns are annualized, value-weighted and are computed over the next year. The model counterpart of B/M is capital divided by the ex-dividend firm market value $k/(v(k, z; \mathbf{S}) - d(k, z; \mathbf{S}))$, where dividend $d(k, z; \mathbf{S})$ is defined as in footnote 8. Model moments are averages across 100 model simulations with 500 quarters each; 200 first quarters were discarded to reduce the impact of initial conditions. Data moments are from Kenneth French's website and correspond to 1964-2019; returns have been corrected for inflation.

5.6 Value Premium

This section demonstrates that the model accounts for the cross-section of stock returns. In particular, the model is capable of generating a value premium of about 4 percent per year, a number close to that in the data. Table 7 provides summary statistics on quintile B/M-sorted portfolios. The first three columns demonstrate that, both in the model and in the data, expected returns are monotonically increasing in B/M. The second column shows that the value premium (quintile 5-1 return) is about 1.7 percent in the version of the model without microeconomic disasters. However, the value premium in the model with jumps is 3.9 percent per annum, which is close to 4.2 percent in the data. The last three columns show that the model tracks the data well in terms of the volatility of returns.

It is instructive to look at the definition of value in the model. Specifically, panel (A) of Figure 4 shows that value firms (high B/M) predominantly have low productivity and are stuck with high stocks of (temporarily) unproductive capital. In the model, there are only 2 dimensions of the cross-sectional heterogeneity—capital and (idiosyncratic) productivity—and the first panel essentially indicates that value and growth firms mainly differ along the productivity dimension. At the same time, capital is slowly-moving due to the presence of convex and non-convex capital adjustment costs, and its role in the B/M heterogeneity across firms is limited. Panel (B) shows that expected returns decline strongly in productivity.

Figure 4: Firm States, B/M, and Expected Returns



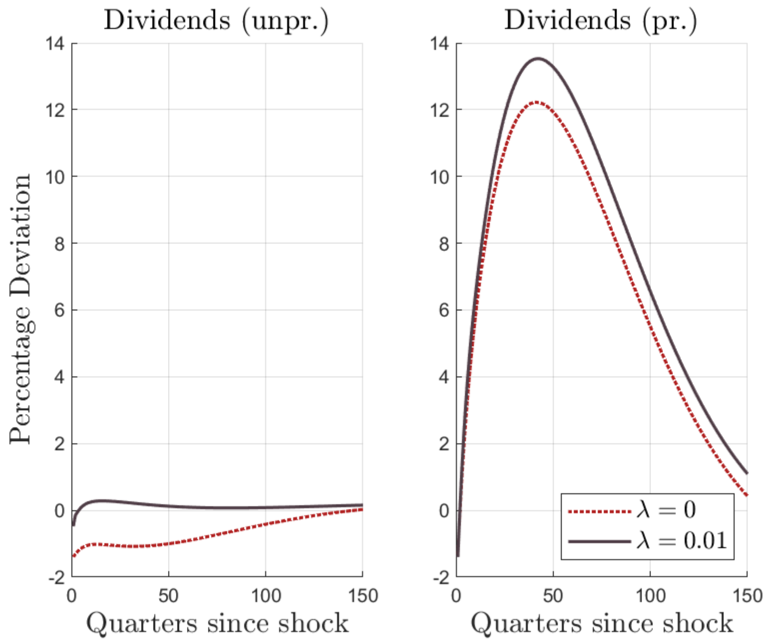
(A) B/M and productivity (B) Expected returns and productivity

Notes: Figure 4 consists of two panels. Panel (A) plots the relationship between B/M and idiosyncratic productivity for firms with low, medium and high levels of capital k_{it}. Low, medium and high capital are the 25-, 50-th and 75th percentiles of simulated data. B/M is capital divided by the ex-dividend firm market value $k/(v(k, z; \mathbf{S}) - d(k, z; \mathbf{S}))$, where dividend $d(k, z; \mathbf{S})$ is defined as in footnote 8. Panel (B) plots the relationship between expected returns (annualized) against idiosyncratic productivity (separately for 3 different levels of capital, like in Panel (A)).

In order to demonstrate why value firms earn higher returns than growth firms, we plot impulse-response functions of average dividends for productive and unproductive firms to a negative TFP shock. For the purpose of this exercise, we call a firm productive if its idiosyncratic productivity is above 0.2, and unproductive in case it is lower than -0.2. We chose to plot average dividends to eliminate the effect of time-varying masses of unproductive and productive firms in the aftermath of an aggregate shock. Figure 5 demonstrates two things. First, average dividends of unproductive firms fluctuate much less relative to productive firms; the cash flow of highly productive firms is strongly countercyclical. Thus, unproductive firms are riskier, and investors require higher compensation to hold those stocks. This is the key reason for why value premium emerges in our framework.

Moreover, an increase in λ makes dividends of all firms more countercyclical, but the impact on unproductive firms is weaker, and their dividend stream becomes nearly acyclical. This reflects the fact that these firms have very low output and investment, and, thus, lower aggregate productivity has a limited impact on both of those components. Provided that

Figure 5: Impulse-Response Functions of Average Dividends for Productive and Unproductive Firms



Notes: Figure 5 plots impulse-response functions of average dividends for productive and unproductive firms to a one standard deviation negative innovation to aggregate TFP. Model with microdisasters ($\lambda = 0.011$) is solid black, model without disasters ($\lambda = 0$) is dotted red. Productive firms ("pr.") are those with idiosyncratic productivity above 0.2, unproductive firms ("unpr.") have productivity lower than -0.2.

higher values of λ make marginal utility more volatile (see Section 5.5), this generates higher returns on value (unproductive) firms. At the same time, dividends of productive firms become even more countercyclical as λ rises, since the presence of large negative shocks induces them to cut their investment stronger. Our simulations reported in Table 7 demonstrate that average returns of the two bottom B/M quintiles slightly decrease as λ rises. Note how these results echo an earlier discussion on the cyclical properties of aggregate investment and dividend rates in Section 5.2; there we showed that jumps increase the volatility of dividends for productive firms, while the impact on unproductive firms is muted. In sum, microeconomic disasters increase the value premium both by raising returns of value firms and slightly reducing returns of growth stocks.

Value vs. Profitability Premium In the data, firms with higher profitability ratios—defined as the ratio of profits to total assets—tend to earn higher average returns; this is often referred to as profitability premium (Novy-Marx, 2013). This phenomenon has recently received considerable attention in the literature (e.g., Bouchaud, Krueger, Landier and Thesmar, 2019; Kogan, Li and Zhang, 2022). However, it turns out that it is difficult for production economies, including the model developed in this paper, to simultaneously account both for the value and profitability premiums; the key reason is that productive firms in this class of models are both low B/M (growth) and highly profitable. Thus, it is problematic to jointly account for low expected returns of growth stocks and high returns of profitable firms. One way to rationalize both premiums in a production economy setting is to introduce persistent and transitory shocks to idiosyncratic productivity (Ai, Li and Tong, 2021); the authors show that firms' market value is more responsive to the former type of shocks, whereas profitability—to the latter. As a result, this decouples productivity from B/M and allows the model to generate both types of premiums.

5.7 Investment Premium

Provided that less productive firms earn higher returns than more productive firms, the model naturally accounts for the investment premium. In the data, stocks of firms with lower prior investment on average earn higher returns as compared to firms with higher prior investments (Fama and French, 2015); the quintile 1-5 return is more than 3 percent per annum (column (1) in Table 8).

In the model, idiosyncratic productivity accounts for the cross-sectional heterogeneity of firms, and is, thus, tightly linked to investment decisions of firms. For instance, Figure C7 in Appendix demonstrates that investment decisions of firms are strictly increasing in productivity at all levels of capital, but especially so for firms with low capital. We have already shown that expected returns decline strongly in productivity; this leads to a negative relationship between investment rates and expected returns.

We find that the model without microeconomic disasters ($\lambda = 0$) generates a 1-5 quintile return of 3.4 percent per annum (column (2) in Table 8); this accords well with the investment premium found in the data. The model with disasters ($\lambda = 0.011$) generates an investment

Table 8: Summary Statistics for 5 Investment Sorted Portfolios

	$\mathbb{E}[R_{port}]$			$\sigma[R_{port}]$		
		Model			Model	
Portfolio	Data	$\lambda = 0$	$\lambda = 0.011$	Data	$\lambda = 0$	$\lambda = 0.011$
Low	10.5	7.3	8.9	18.8	18.6	18.1
2	8.6	6.7	8.5	14.9	17.9	17.3
3	8.0	5.8	6.5	15.8	17.2	16.0
4	8.0	4.9	4.9	17.0	16.7	15.3
High	7.2	3.9	3.8	22.0	16.2	14.7

Notes: Table 8 reports the mean and the standard deviation of returns for 5 value-weighted portfolios using firm-level capital growth. Returns are annualized, value-weighted and are computed over the next year. Specifically, portfolios are formed at the start of year t based on the growth rate of capital from the end of year $t-2$ to the end of year $t-1$. Model moments are averages across 100 model simulations with 500 quarters each; 200 first quarters were discarded to reduce the impact of initial conditions. Data moments are from Kenneth French's website and correspond to 1964-2019; returns have been corrected for inflation.

premium of about 5 percent, and this increase is predominantly driven by a much higher return on stocks in the first two quintiles (least productive firms). This mirrors the logic for why an increase in the value premium is driven by the top quintile of B/M firms; in both cases, microeconomic disasters have a more pronounced impact on the riskiness of unproductive firms.

5.8 Persistence of Small vs. Large Shocks

As we have documented in Section 2, the extent of mean-reversion of firm-level shocks varies depending on the size of the shock. In particular, the data reveal that large shocks are more transitory than small shocks; this result is pervasive and holds across the entire firm-size distribution. In this section, we explore how persistence of different types of shocks affects the cross-section of stock returns in our model.

To fix ideas, we refer to realizations of the normal random variable ε in Equation (2) as "small" shocks; at the same time, the jump component J is referred to as a "big" shock. It is straightforward to explore the role of persistence of small shocks; one needs to compare the performance of models with different values of ρ_z when the jump component is absent, $\lambda = 0$. The first column in Table 9 demonstrates how average returns of B/M sorted portfolios change when ρ_z increases from the benchmark value of 0.88 to 0.92 (λ is set equal to 0). We

Table 9: Persistence of Idiosyncratic Shocks: Impact on Cross-section of Stock Returns

	B/M Sorted		Investment Sorted	
Portfolio	Small Shocks	Big Shocks	Small Shocks	Big Shocks
Low	–1.1	–1.8	+0.5	+2.7
2	–1.2	–0.6	+1.7	+3.2
3	–0.9	+1.0	+0.3	+2.7
4	–0.3	+3.6	–0.9	+0.1
High	+1.4	+9.2	–1.6	–0.5

Notes: Table 9 reports the change in average returns for 5 B/M and investment sorted portfolios when persistence of idiosyncratic shocks increases from the benchmark value of 0.88 to 0.92. The construction of portfolios follows the same steps as in Tables 7 and 8. "Small shocks" columns report the change in portfolio returns between models $\{\lambda = 0, \rho_z = 0.92\}$ and $\{\lambda = 0, \rho_z = 0.88\}$. "Big shocks" columns report the following double-difference in portfolio returns:

$$[\{\lambda = 0.011, \rho_z = 0.92\} - \{\lambda = 0.011, \rho_z = 0.88\}] - [\{\lambda = 0, \rho_z = 0.92\} - \{\lambda = 0, \rho_z = 0.88\}] .$$

Moments are averages across 100 model simulations with 500 quarters each; 200 first quarters were discarded to reduce the impact of initial conditions.

find that the value premium increases by 2.5pp; average returns of growth stocks decrease, while returns of value firms rise. We repeat this exercise for investment sorted portfolios is column (3); the investment premium increases by a comparable amount of 2.1pp.

We now isolate the role of persistence of large shocks by considering a double-difference of portfolio returns. Specifically, we first compute the difference in returns varying the degree of persistence in the model with jumps ($\lambda = 0.011$) and without jumps ($\lambda = 0$) separately. Intuitively, in the first case we capture the role of higher persistence for both big and small shocks, whereas in the second case we measure the role of higher persistence for small shocks only. Subsequently, we take the difference of these two differences—the second difference—which isolates the effect of higher persistence for the jump component. The second and fourth columns of Table 9 demonstrate that persistence of the jump component plays a major role; the value and investment premiums increase by 11 and 3.2pp, respectively. Our simulations also show that the effect of higher persistence is primarily driven by elevated returns of the least productive firms, i.e. more risky firms. In general, these results illustrate that persistence of shocks plays a paramount role for the cross-section of stock returns, and, thus, it is important to put discipline on mean reversion of shocks of different sizes for the quantitative success of asset pricing models.

6 Application: Supply Chain Disruptions and Disasters

This section studies the impact of supply chain disasters on asset prices by combining our quantitative model developed in Section 3 with a large Bill of Lading data on importing activity of U.S. firms.

We start with the description of the data in Section 6.1, and discuss how we measure supply chain disruptions in Section 6.2. In Section 6.3, we document that supply chain disruptions impair firm-level performance. Finally, we study the impact of supply chain disasters on asset prices in Section 6.4.

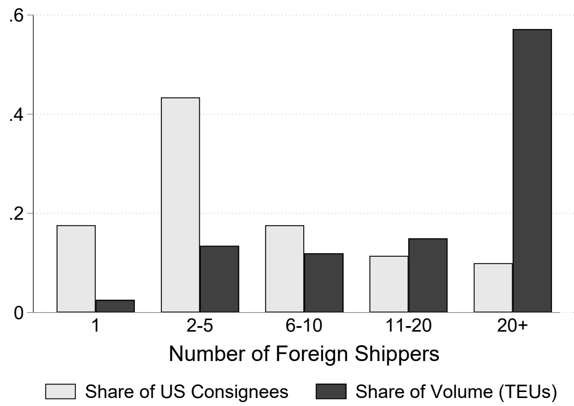
6.1 Data

Background S&P Global Panjiva is a bill of lading (BoL) dataset that covers over a billion of shipment-level records traded across borders. While Panjiva provides access to shipment-level data for 14 countries, in this paper we work with U.S. imports; the raw data include nearly 200mln records and span the period from 2007 to the present time. The U.S. data only include seaborne import, and, therefore, account for about one half of the overall U.S. import.[9]

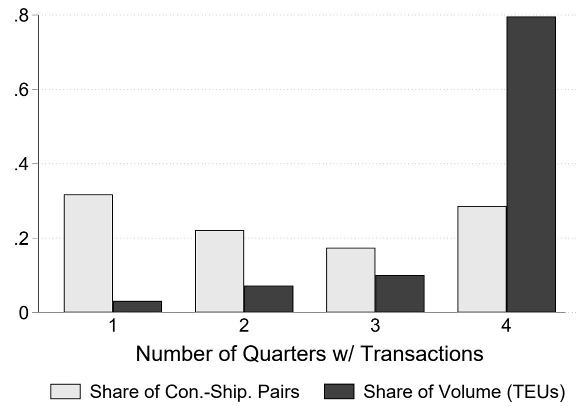
The data represent bills of lading from U.S. Customs and Border Protection (CBP), which are freely available under the Freedom of Information Act of 1966 (FOIA). A BoL is a legal document that serves as a record that a shipment has been transported from its origin to its final destination. Each BoL requires companies to fill out various fields, including shipper(exporter)/consignee(importer) name and address, description of the good(s), vessel name, transport company name, ports of lading (loading) and unlading (unloading), weight,

[9] Flaaen, Haberkorn, Lewis, Monken, Pierce, Rhodes and Yi (2021) also argue that these data accord well with U.S. Census Bureau aggregate series. In principle, using the BoL data for Mexico one can account also for an important proportion of land shipments.

Figure 6: Characteristics of Seaborne Import by U.S. Firms



(A) Distribution of firms by num. of shippers



(B) Frequency of transactions by trade pair

Notes: Figure 6 consists of two panels. Panel (A) plots the distribution of U.S. firms (consignees) by the number of foreign shippers (gray bars) in 2019. Panel (B) plots the distribution of trade pairs with respect to transaction frequency in 2019; the sample is restricted to those pairs which traded at least once in 2018. Black bars show shares of total import by volume (TEUs) that each category accounts for.

quantity, and container information. Panjiva collects, parses and stores raw data in an accessible way. On top of providing the raw data, Panjiva also imputes several additional variables, including, for example, shipment volume in twenty-foot equivalent units (TEUs); the imputation is based on the container information and other shipment characteristics. Panjiva data are updated several times a week; thus, the timeliness of their release represents an advantage over the official U.S. trade data. See Appendix A.2 for additional details about Panjiva.

Sample Selection Throughout the analysis, we work at the level of the ultimate parent company; to this end, we use the the cross-reference file provided by Panjiva to associate a head company ID with each consignee ID; this also allows us to link shipment data with Compustat and study the implications of supply chain disruptions for asset pricing.

We impose several selection criteria to the raw data. First, we account for the redacting activity of U.S. consignees; the firms may requests that the U.S. Customs and Border Protection remove their identity in the shipper or consignee field. Specifically, we exclude firms if the number of unique shippers exceeds the mean ± 3 standard deviations at any point of time.[10] This way, we drop companies which have large spikes (up or down) in the number of shippers which may be indicative of the redacting activity.

Second, given our interest in measuring supply chain disruptions, we focus on companies which actively import; thus, firms which do not to make transactions frequently enough (in at least 50 percent of quarters they are present in the sample) are also excluded. Finally, we exclude carriers and logistic companies; it turns out that when a carrier handles a shipment end-to-end, then this logistic company will be recorded as a consignee. To address this issue, we hand-created a list of the largest 100 logistic companies, and subsequently excluded observations where these logistic companies/freight forwarders are recorded as consignees. The remaining sample selection details are relegated to Appendix A.2.3.

Table 10 reports summary statistics for select years. Overall, the data cover approximately 50,000 ultimate parent firms. In the data, firms are highly right-skewed in terms of shipments, import volume, and the number of shippers. The average firm makes about 80 transactions per year, which collectively occupy 200 containers (twenty-foot equivalent units, TEUs). The mean firm has 10 unique shippers per year, while the median one has only 4. Furthermore, a significant share of firms only have 1 shipper, while consignees in the top decile import from more than 20 firms.

Figure 6 visualized the nature of the importing activity of firms in our sample. Panel (A) demonstrates that 80 percent of firms have fewer than 10 unique shippers; these firms collectively account for about 35 percent of the total import volume. Approximately 10 percent of U.S. consignees trade with more than 20 shippers and they account for almost 60 percent of the overall import volume. Panel (B) shows that about one-third of trade pairs transact every quarter, and that these pairs are important in the aggregate since 80 percent of import occurs between frequent trade partners.

A large part of our analysis is focused on a subset of consignees which can be linked with the universe of Compustat firms. In order to merge Panjiva data with Compustat, we use the crosswalk sourced from WRDS. The crosswalk contains the starting and ending date for

[10] The mean and standard deviation are computed individually for each firm.

Table 10: Summary Statistics, Select Years

Year 2010						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	46946	0.074	0.390	0.002	0.016	0.146
Volume (1000s TEUs)	46946	0.171	1.669	0.001	0.017	0.267
Number of shippers	46946	9.916	24.064	1.000	4.000	21.000
Year 2015						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	51688	0.092	0.622	0.003	0.017	0.168
Volume (1000s TEUs)	51688	0.218	1.937	0.001	0.020	0.330
Number of shippers	51688	10.340	28.983	1.000	4.000	22.000
Year 2020						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	49014	0.084	0.597	0.002	0.015	0.155
Volume (1000s TEUs)	49014	0.205	1.789	0.001	0.019	0.330
Number of shippers	49014	9.418	24.223	1.000	4.000	20.000

Notes: Table 10 reports summary statistics for the underlying sample of U.S. firms for years 2010, 2015 and 2020. The variables have the following interpretation: `Shipments`, total annual number of shipments (in 1000s), `Volume`, total annual volume in 1000s TEUs, `Number of shippers`, total annual number of unique shippers.

every ultimate parent company ID – GVKEY pair; we use the link which was active in a given time period. The sample of public firms exhibits broadly the same patterns as the bigger sample (see Figure C1 in Appendix).

6.2 Supply Chain Disruptions

We now describe how we identify both supply chain disruptions and disasters using our comprehensive micro-level data on individual transactions.[11] We say that a supply relationship between consignee i and shipper j is *disrupted* in quarter t if this pair *(i)* was active in each of the preceding 4 quarters, *(ii)* was inactive in t, and *(iii)* was active in $t+1$. This choice reflects several considerations. On the one hand, we require trade relationships to be well-established and frequent (condition *(i)*). Otherwise, it is difficult to separate an event of disruption from the infrequent nature of trade activity for a given consignee-shipper pair.

[11]Measuring supply chain disruptions is not a trivial task because these shocks can occur for multiple reasons, including natural disasters and weather-related problems (Carvalho, Nirei, Saito and Tahbaz-Salehi, 2021), bankruptcy of the counteragent (Yang, Birge and Parker, 2015), bankruptcy of a carrier (Kwon, 2021), and many others (see, for example, Hendricks and Singhal, 2005). Our metric is attractive since it allows us to capture disruptions of different natures.

On the other hand, we need to ensure that the event of inactivity at time t does not merely reflect the consignee's choice whereby it finds a better supplier and terminates import from a given shipper (condition *(iii)*). In principle, disruptions may last longer than one quarter; such events are not classified as disruptions given the baseline definition. We performed extensive sensitivity analysis in Appendix A.3 where we, for instance, required the trade relationship to be active for 3 out of 4 quarters between $t+1$ and $t+4$. The results are qualitatively similar. We chose the first definition as the baseline because it allows us to identify more disruptions toward the end of the sample period which is of particular importance for this study.

Furthermore, we chose to measure disruptions at quarterly frequency in order to avoid potential complications arising from seasonality patterns; these considerations are likely to be less of a concern at lower frequencies. Additionally, quarterly frequency matches the length of the time period both in the model and in the firm-level data (Compustat Fundamentals Quarterly).

Additional Sample Selection and Summary Statistics Given the way we measure supply chain disruptions, we chose to focus on firms which actively import. As we have seen earlier, importing activity is heavily concentrated among firms with 20 or more unique shippers. Thus, we further restrict our sample to firms which on average have at least 20 shippers; we impose this criterion both for the full sample and the sample with public firms. Table 11 reports summary statistics for year 2019 (statistics for other years are in Appendix D); the top panel corresponds to all firms, whereas the bottom one is restricted to the Compustat universe. It is clear that even though we look at very large firms (with average sales of public firms of over \$16bn), the distribution of firms with respect to shipping activity is highly right skewed. The median firm makes about 250 more transactions than the firm in the bottom decile, whereas the firm in the 90^{th} percentile makes 1200 more transactions than the median one (the corresponding numbers for Compustat firms are 500 and 2500, respectively). Firms are even more skewed in terms of the import volume. On average, firms

Table 11: Summary Statistics, 2019

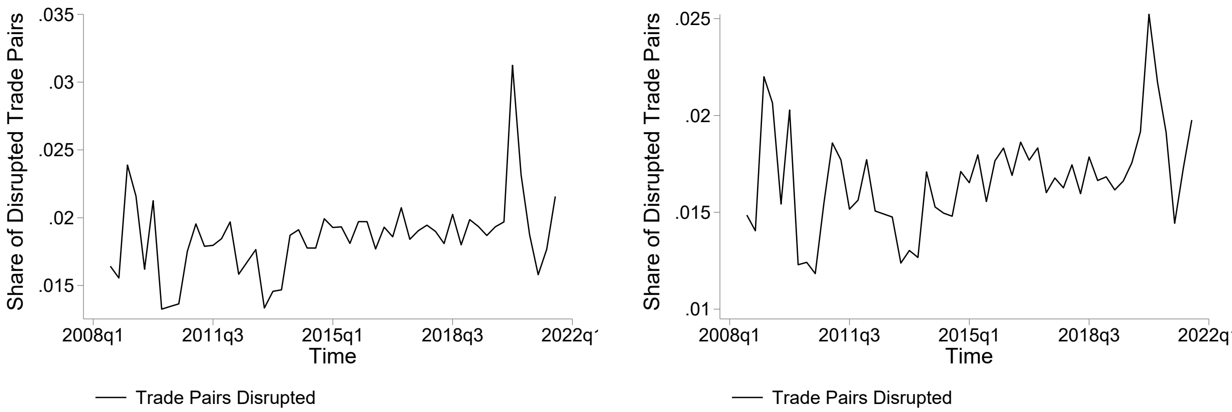
Full Sample						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	2919	0.684	2.464	0.015	0.275	1.414
Volume (1000s TEUs)	2919	1.533	6.757	0.016	0.359	3.256
Number of shippers	2919	63.0	84.8	6.0	46.0	120.0
Share redacted	2919	0.095	0.194	0.000	0.011	0.321
Number of disruptions	2919	0.565	0.899	0.000	0.250	1.500
Share of import disrupted	2482	0.019	0.049	0.000	0.006	0.046
Compustat						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	420	1.298	2.091	0.069	0.594	3.046
Volume (1000s TEUs)	420	2.842	5.640	0.072	1.054	7.057
Number of shippers	420	102.6	123.8	19.0	67.0	216.5
Share redacted	420	0.115	0.198	0.000	0.027	0.359
Sales(bn)	424	16.44	37.51	0.49	4.36	37.72
Total assets(bn)	424	44.23	199.30	0.52	4.59	61.13
Quarterly sales growth	410	0.003	0.055	-0.034	0.007	0.040
Number of disruptions	424	0.582	1.101	0.000	0.000	1.750
Share of import disrupted	424	0.005	0.013	0.000	0.000	0.015

Notes: Table 11 reports summary statistics for the underlying sample of U.S. firms for year 2019. The variables have the following interpretation: `Shipments`, total annual number of shipments (in 1000s), `Volume`, total annual volume in 1000s TEUs, `Number of shippers`, total annual number of unique shippers, `Share redacted`, average quarterly share of observations with missing shipper identifier, `Sales`, total annual sales, `Total Assets`, average quarterly total assets, `Quarterly sales growth`, average quarterly arc sales growth, `Number of disruptions`, average quarterly number of disrupted pairs, `Share of import disrupted`, average quarterly share of total import accounted for by disrupted trade pairs. Nominal variables have been converted to real ones using the Producer Price Index with 2015 being the base year.

have 63 unique shippers in year 2019, with the median number of 46. Firms in the top decile have more than 120 shippers. Not surprisingly, public firms have more diversified supply networks (average number of shippers is about 100), and import more. Finally, about 2 percent of import gets disrupted per quarter, this share is four times lower for public firms, reflecting a larger overall import volume. The average number of trade pairs being disrupted is about 0.6 per quarter.

Supply Chain Disruptions in U.S. Firms Panel (A) of Figure 7 plots the evolution of the share of trade pairs being disrupted at quarterly frequency from 2008 to 2021. The probability of a supply chain disruption varies between 1.5 percent to 3 percent per quarter during the sample period. There are noticeable spikes, however. The first one is the Great

Figure 7: Share of Disrupted Trade Pairs



(A) Full sample (B) Compustat sample

Notes: Figure 7 consists of 2 panels. Panel (A) plots shares of trade pairs being disrupted by quarter according to the definition provided in Section 6.2 for the full sample. See Appendix A.2.3 for details on sample construction. Panel (B) plots the same object for the Compustat subsample.

Recession episode 2008-2009; these disruptions likely reflect financial hurdles on the side of exporters and/or importers given the nature of the global recession. Furthermore, we see a rapid increase in 2011 which can be plausibly attributed to two natural disasters: the Tohoku earthquake in Japan and the flooding in Thailand. These countries are major auto and electronics producers; internal shock there had a pronounced effect on global production chains throughout the world. Finally, a rise in the share of disrupted trade pairs in 2020 may reflect numerous factors, including regulatory constraints and bottlenecks (e.g., in ports of Los Angeles and Long Beach).[12] Our disruption measure is capable of identifying supply chain disruptions of different natures. Panel (B) exhibits similar patterns for U.S. public firms.[13]

Comparison to Other Aggregate Indices We now compare the dynamics of identified supply chain disruptions against two other aggregate indices of supply chain disruptions.

[12]These ports account for about one half of the total seaborne U.S. import.

[13]We also analyzed the dynamics of supply chain disruptions disaggregated to the sector-level; Figure C16 in Appendix plots the share of supply relationships being disrupted for several NAICS 2-digit industries. While the resulting series are somewhat noisier than the aggregate one (potentially reflecting a relatively small sample size of public firms), the figure reveals a sufficiently pronounced cross-sectoral heterogeneity in the dynamics of supply chain disruptions.

We first consider the Global Supply Chain Pressure Index, hereafter GSCPI (Benigno, di Giovanni, Groen and Noble, 2022).[14] That index is constructed using the principal component analysis of 27 time series that are meant to capture factors that put pressure on global supply chains, both domestically and across borders. For example, the authors use data on shipping costs of raw materials, container shipping rates, delivery time and backlogs indices for several major economies. Furthermore, the authors incorporate the demand effect by regressing underlying series on factors which likely capture the extent of customer demand for firms' products (i.e., indices of new orders). Figure C2 in Appendix demonstrates that the series align well both for the full sample and the Compustat subsample, and that both metrics broadly capture the same patterns: an increase in disruptions in 2011, an upward trend between 2015 and 2018, and, finally, a massive spike in 2020-2021.

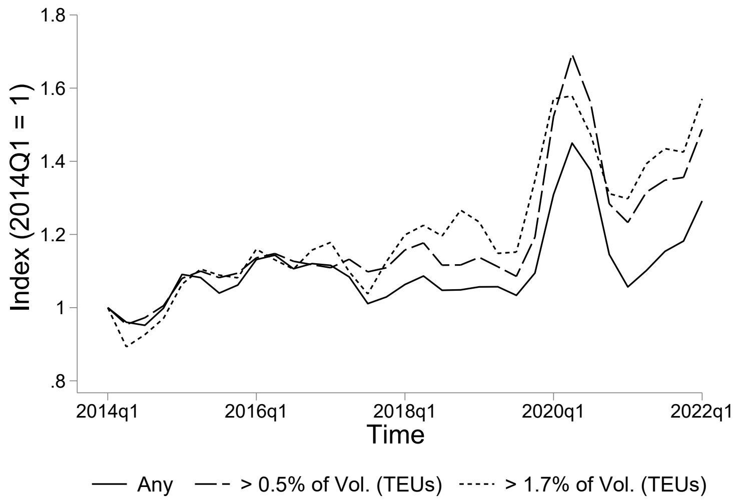
We also compared our results against the Bloomberg Supply Constraint Indicator, an aggregate index representing a single common factor extracted from a set of supply-related indicators.[15] The underlying data include information on supplier deliveries, business backlogs, prices, Commodity Research Bureau BLS raw-industrial spot indices, investment-to-sales ratio from the Census Bureau, and total unemployed workers from the BLS. While negative values mean that supply is relatively abundant, positive values are indicative of constraints. Provided that supply chain disruptions do not manifest themselves immediately, but rather lead to supply shortages in the future, we consider a one-year lead of the Bloomberg's indicator. Figure C3 shows that identified supply chain disruptions and supply shortages track each other well. We, thus, take this as an additional supporting piece of evidence that our metric successfully captures supply chain disruptions.

Disaggregating Disruptions The share of supply relationships being disrupted is a broad measure of supply chain disruptions that ignores both their size and importance for firms. Our comprehensive data allow us to study not only the incidence but also the severity of disruptions by analyzing the data on the TEU volume. Figure C4 in Appendix recomputes

[14] https://www.newyorkfed.org/research/gscpi.html.

[15] https://www.bloomberg.com/news/terminal/R5MA2CT0AFB8.

Figure 8: Large Disruptions Have Recently Become More Common



Notes: Figure 8 plots three lines. The solid line plots the share of trade pairs being disrupted. The dashed line corresponds to the probability of a disruption that accounts for at least 0.5 percent of the firm-level trade volume over the preceding 4 quarters. The dotted line does the same but for disruptions exceeding 1.7 percent of firms' total import volume (corresponds to the average level of disruptions plus 3 standard deviations of 0.4 percent). Time series have been normalized to 1 in 2014Q1. The series have been lowess smoothed with a parameter 0.15.

shares of supply disruptions depending on which fraction of firm's import volume those pairs accounted for over the preceding 4 quarters. Specifically, we consider two thresholds of 0.5 percent and 1.7 percent of firm import volume; these numbers represent the mean disruption size and the mean plus 3 standard deviations of 0.4 percent, correspondingly.[16] We report results both for the full sample and the Compustat subsample. Additionally, we overlay the resulting series with the GSCPI index for comparability. Panels (A) and (C) show that the two metrics track each other slightly closer when we look at disruptions of 0.5 percent and larger. At the same time, panels (B) and (D) demonstrate that large disruptions were very common during the Great Recession and shortly afterwards; our index exceeds 2 standard deviations from the average level at that time. In general, we see that the two series are less well aligned in case of large disruptions. In Figure C5, we overlay our series with the Bloomberg Supply Constraint indicator and find broadly similar patterns.

Figure 8 further illustrates how the probability of disruptions has changed over time since

[16] The mean and the standard deviation are calculated across firms by pooling all years.

2014Q1 depending on which fraction of firm import volume that pair accounted for over the preceding 4 quarters. In particular, we see that all three series exhibit a sharp increase in 2020. Interestingly, however, the probability of large disruptions (those which account for at least 0.5 percent of trade volume) has increased substantially more than the odds of any disruption (about 80 percent gain relative to 2014 vs. 45 percent in case of any disruption). In summary, the probability of very large supply chain disruptions nearly doubled over the last several years.

6.3 Supply Chain Disruptions and Firm Performance

We next study how supply chain disruptions are associated with firm-level performance. To this end, we turn to our sample with public firms and estimate the following specification:

$$\widetilde{\Delta} Sales^{t}_{i,t-1} = \beta \mathbf{1}_{\text{Disruption}_{i,t}} + \lambda \mathbf{X}_{i,t} + \varepsilon_{i,t}, \tag{18}$$

where the dependent variable is the arc-growth measure of sales,

$$\widetilde{\Delta} Sales^{t}_{i,t-1} = \frac{Sales_{i,t} - Sales_{i,t-1}}{\frac{1}{2}(Sales_{i,t} + Sales_{i,t-1})}.$$

This measure is attractive in that it is bounded between -2 and 2, thereby avoiding arbitrary winsorization of outliers (Davis, Haltiwanger and Schuh, 1996). The key independent variable $\mathbf{1}_{\text{Disruption}_{i,t}}$ is a dummy variable which takes the value of 1 if firm i experiences a disruption of a supply relationship at time t. Coefficient β measures how the average sales growth differs between firms with and without disruptions. The vector of controls $\mathbf{X}_{i,t}$ includes an intercept, as well as time (year-quarter) and firm fixed effects. We also control for size effects by including the logarithm of total assets.

Column (1) of Table 12 shows that firms experiencing a disruption on average grow 0.6pp slower. Furthermore, in column (2) we add firm fixed effects and, thus, explore the role of disruptions not between but within firms; the coefficient estimate remains to be significant

Table 12: Sales Growth and Supply Chain Disruptions

	$\widetilde{\Delta} Sales^{t}_{i,t-1}$			$\widetilde{\Delta} Sales^{t-1}_{i,t-2}$	$\widetilde{\Delta} Sales^{t+1}_{i,t-1}$	$\widetilde{\Delta} Sales^{t+2}_{i,t-1}$	$\widetilde{\Delta} Sales^{t+3}_{i,t-1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbf{1}_{\text{Disruption}_{i,t}}$	-0.0055**	-0.0076**		-0.0022	-0.0118***	-0.0096**	-0.0044
	(0.003)	(0.003)		(0.003)	(0.004)	(0.004)	(0.005)
Share disrupted$_{i,t}$			-0.3250**				
			(0.135)				
Year-Quarter FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	—	✓	✓	✓	✓	✓	✓
R^2	0.048	0.061	0.061	0.060	0.071	0.102	0.161
N	20595	20593	20593	20240	20181	19773	19356

Notes: Table 12 reports results of OLS estimation of Equation (18). The dependent variable $\widetilde{\Delta} Sales^{t}_{i,t-1}$ is the arc-growth of firm-level sales between quarters $t-1$ and t. The independent variable $\mathbf{1}_{\text{Disruption}_{i,t}}$ is a dummy variable, which takes a value of 1 if firm i experienced any supply chain disruption at time t. Furthermore, Share disrupted$_{i,t}$ measures the share of total import that disrupted supply relationships accounted for over the preceding 4 quarters. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

at 5 percent level and increases up to 0.76pp. Economically, the effect is large: The average quarterly sales growth in our sample is about 0.5 percent.

The first set of results treated all disruptions on equal footing; however, it is natural to suspect that firms perform much worse in case of large disruptions. We further regress sales growth on the share of import that disrupted trade relationships accounted for over the last 4 quarters; this variable is equal to 0 for firms experiencing no disruptions. Column (3) shows that a 10pp increase in the share of disrupted import is associated with a nearly 3pp slower sales growth. The effect is quantitatively large and suggests that the average effect in columns (1)-(2) is driven by rare but massive supply chain disruptions.

So far, we looked at the contemporaneous effect, whereby supply frictions were related to the sales growth in the same period; the remainder of the table explores the impact of disruptions on sales growth at various horizons. First, in column (4) we relate the sales growth from $t-2$ to $t-1$ with supply chain disruptions taking place in t and find no statistically significant relationship between the two variables. We take this as suggestive evidence that our measured supply chain disruptions are to a large extent unexpected by firms.

Furthermore, columns (5) and (6) demonstrate that the effect of disruptions is not short-

Table 13: Sales Growth and Probability of Disruption

	$\mathbf{1}_{\text{Disruption}_{i,t}>0.005}$	$\mathbf{1}_{\text{Disruption}_{i,t}>0.012}$	$\mathbf{1}_{\text{Disruption}_{i,t}>0.017}$	$\mathbf{1}_{\text{Disruption}_{i,t}>0.036}$
	(1)	(2)	(3)	(4)
Sales growth quintile 2	-0.0045	-0.0061	-0.0076	-0.0049
	(0.009)	(0.007)	(0.006)	(0.004)
Sales growth quintile 3	-0.0149*	-0.0135*	-0.0125*	-0.0098**
	(0.009)	(0.007)	(0.007)	(0.005)
Sales growth quintile 4	-0.0153*	-0.0137*	-0.0116*	-0.0095**
	(0.009)	(0.007)	(0.007)	(0.005)
Sales growth quintile 5	-0.0218***	-0.0120	-0.0121*	-0.0082*
	(0.008)	(0.008)	(0.007)	(0.005)
Constant	0.1593***	0.1023***	0.0858***	0.0452***
	(0.007)	(0.006)	(0.005)	(0.004)
Year-Quarter FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
State FE	✓	✓	✓	✓
R^2	0.107	0.063	0.052	0.029
Observations	20493	20493	20493	20493

Notes: Table 13 reports results of OLS estimation of Equation (19). The dependent variable $\mathbf{1}_{\text{Disruption}_{i,t}}$ is a dummy variable, which takes a value of 1 if firm i experienced any supply chain disruption at time t. Independent variables $\{\mathbf{1}_{\widetilde{\Delta} Sales_{i,t-1}^{t+1} \in Q_q}\}$ are dummy variables and take a value of 1 if the growth rate of a firm i from $t-1$ to $t+1$ was in the q-th quintile of the sales growth distribution. Disruption threshold for column (1) is 0.5% (mean size of disruption in Compustat sample), threshold for column (2) is 1.2% (mean size of disruption in full sample), threshold for column (3) is 1.7% (mean size of disruption $+3\sigma$ in Compustat sample), threshold for column (4) is 3.6% (mean size of disruption $+3\sigma$ in full sample). Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

lived but persistent in that the adverse effect is present both in quarters $t+1$ and $t+2$. The quantitative magnitude of the estimates in these two columns shows that the impact of disruptions increases over time and reaches its maximum in the quarter following the disruption. Finally, column (7) indicates that the effect of a disruption mean-reverts by quarter $t+3$. Thus, the presented evidence displays that supply chain disruptions are associated with a pronounced decline is sales growth, and that the effect is persistent as it only dissipates at the horizon of 3 quarters.

Share of Firms with Disruptions by Sales Growth Quintile We have demonstrated that disruptions are associated with a pronounced decline in sales growth. The richness of our dataset allows us to more comprehensively analyze the joint behavior of sales growth, supply chain disruptions and, in particular, large disruptions. Specifically, we evaluate which fraction of firms with a given sales growth also experience disruptions of various sizes.

To operationalize this, we draw on the Compustat sample and split observations into 5 quintiles based on the sales growth from $t-1$ to $t+1$. We then estimate the following model:

$$\mathbf{1}_{\text{Disruption}_{i,t}>\widetilde{d}} = \sum_{q=2}^{5} \beta_q \mathbf{1}_{\widetilde{\Delta} Sales_{i,t-1}^{t+1} \in Q_q} + \lambda \mathbf{X}_{i,t} + \varepsilon_{i,t}, \tag{19}$$

where Q_q denotes the quintile of sales growth, $q \in \{1, \ldots, 5\}$. The vector of controls $\mathbf{X}_{i,t}$ includes an intercept, as well as time (year-quarter), industry (at NAICS 4-digit level) and state fixed effects. A constant in this regression measures the share of firms in the bottom 20 percent of the sales growth distribution that also experience supply chain disruptions; coefficients $\{\beta_q\}_{q=2}^{5}$ then capture how different this share is for firms in other quintiles. Parameter $\widetilde{d}$ determines the size of disruptions.

Table 13 reports the results. Column (1) shows that among firms in the bottom 20 percent of the distribution, 16 percent of firms also experience disruptions of at least 0.5 percent of recent import volume; this threshold is the average (quarterly) size of a disruption in our Compustat subsample. Besides, the share of firms experiencing a disruption of this size monotonically decreases in quintiles 2-5. Column (2) reports qualitatively similar results for the threshold of 1.2 percent, the mean size of a disruption in the full sample.

We now explore which fraction of firms with various sales growth also experience very large supply chain disruptions, i.e. those which exceed the average size of a disruption plus three standard deviations ($1.7\% = 0.5\% + 3 \times 0.4\%$). Column (3) shows that 8.6 percent of firms in the bottom quintile experience such supply chain disasters; this share is 1.2pp smaller among firms in the top quintile.

We have also experimented using the mean and the standard deviation sourced from the full sample to identify supply chain disasters (column (4)); the corresponding threshold turns out to be twice as large (3.6 percent of recent import volume). In our Compustat sample, in which firms are larger than those in the full sample (see summary statistics in

Table 11), very few firms experience supply chain disruptions that large; we, however, still see a significant fall in the share of firms experiencing these extreme events as we move from the bottom to the top quintile of the sales growth distribution.

6.4 Implications of Supply Chain Disruptions

6.4.1 Parameterizing an Increase in SC Disruptions and Disasters in the Model

We start by discussing how we map our empirical findings from Section 6 to the production economy developed in Section 3.

We let the probability of large negative events λ be comprised of two parts, one is driven by supply chain disruptions (λ_{SC}), whereas the second one captures large negative shocks not related to supply chains (λ_{other}). We assume that the probability of the disaster due to supply chain disruptions, λ_{SC}, is the same as the share of firms experiencing large disruptions in the bottom quintile of the sales growth distribution (column (3) in Table 13). That is, among firms in a disastrous state, 8.6 percent of them also experience supply chain disruptions. We calibrate $\lambda_{SC} = 0.00095$ (8.6 percent of the baseline value of $\lambda = 0.011$).

It is worth emphasizing that this is a fairly conservative way to assess the impact of supply chain disruptions for several reasons. First, in the data, supply chain disruptions are affecting many firms, not only those in a catastrophic state. Moreover, we extrapolate findings from Table 13 across the entire firm-size distribution, thereby allocating the same percentage of large negative events to supply chain disruptions both for small and large firms. In reality, this number can be larger, since public firms are not representative of the entire firm-size distribution in that they are likely to be better shielded against supply chain shocks due to more diversified networks of suppliers. Finally, we have seen that firms with poorer performance are more likely to experience supply chain disasters; thus, the corresponding probability in the very bottom of the sales growth distribution can be higher than the share in the bottom quintile.

In the model, we capture the increased pressure on supply chains and the elevated probability of disruptions by defining a new value of the jump intensity λ' as follows:

$$\lambda' = \lambda_{other} + \Delta \times \lambda_{SC},$$

where Δ measures the growth in the probability of supply chain disruptions. That is, we assume that the probability of catastrophic events not related to supply chains λ_{other} has not changed. Continuing the discussion above, we set $\lambda_{SC} = 0.00095$ and $\Delta = 1.8$, reflecting a near 80% increase in the probability of very large disruptions in the last several years (see discussion in Section 6.2). While the odds of disruptions of various sizes increased somewhat differently over the last several years, we found that the value of Δ anywhere in the range between 1.75 and 2 leads to broadly similar results.

Thus, the new arrival rate of disaster shocks is $\lambda' = 0.01176$; that is, our model captures an 80% increase in the probability of supply chain disruptions with a 6.9 percent increase in the odds of catastrophic events.

6.4.2 Impact on Asset Prices

Aggregate Implications The model with a higher arrival rate of Poisson shocks generates an equity premium of 6.72 percent and a risk-free rate of 0.72 percent (with the mean Sharpe ratio of 0.38). Therefore, in the aggregate, our model attributes a 0.16pp increase in the equity premium and a 0.07pp decline in the risk-free rate to elevated pressures on supply chains observed in the last 3 years.

Even though the rise in the probability of microeconomic disasters leads to a relatively modest increase in the equity premium, the effect is significantly non-uniform in the cross-section. To demonstrate this, we study how value and investment premiums change when λ increases.

Impact on Value Premium The first two columns of Table 14 report average returns for both economies (the baseline economy with $\lambda = 0.011$, as well as the one with $\lambda' = 0.01176$). Remarkably, a higher probability of disasters has virtually no effect on 60 percent of stocks.

Table 14: Summary Statistics for 5 B/M and Investment Sorted Portfolios, Role of Supply Chain Disruptions

	B/M Sorted			Investment Sorted		
Portfolio	λ	λ'	Δ	λ	λ'	Δ
Low	4.7	4.7	0.0	8.9	9.2	0.3
2	4.7	4.7	0.0	8.5	8.8	0.3
3	5.3	5.3	0.0	6.5	6.7	0.2
4	6.3	6.4	0.1	4.9	5.0	0.1
High	8.6	9.1	0.5	3.8	3.7	-0.1

Notes: Table 14 reports the mean and the standard deviation of returns for 5 value-weighted portfolios using B/M and investment. Returns are annualized, value-weighted and are computed over the next year. The model counterpart of B/M is capital divided by the ex-dividend firm market value $k/(v(k,z;\mathbf{S}) - d(k,z;\mathbf{S}))$, where dividend $d(k,z;\mathbf{S})$ is defined as in footnote 8. Numbers are averages across 100 model simulations with 500 quarters each; 200 first quarters were discarded to reduce the impact of initial conditions.

Specifically, the bottom 3 quintiles of B/M portfolios deliver the same expected returns. At the same time, value firms in the top B/M quintile now earn 0.5pp higher returns; this reflects a higher exposure of value firms to large negative shocks.

The higher expected returns for the top book-to-market quintile accord well with the time-series fluctuations in the aggregate dividend rate; we find that the volatility of dividends increases up to 2.9 percent for productivity quintiles 2 through 5 (as compared with 2.8 percent reported in Table 4), whereas the impact of a higher λ on the bottom productivity quintile is essentially zero.

Impact on Investment Premium Naturally, the asymmetric increase in expected returns of unproductive firms relative to productive ones is also reflected in the higher investment premium. The last three columns in Table 14 demonstrate that a 8.6 percent increase in λ leads to a 0.3pp higher returns for the first two quintiles of investment-sorted portfolios, and nearly no impact on firms with high investment rates.

6.4.3 Supply Chain Disruptions and Realized Returns

We now use the identified supply chain disruptions and disasters to study the impact of these events on asset prices. Specifically, we estimate the following specification:

$$r_{i,t} = \beta_0 + \beta_1 \mathbf{1}_{\text{High}_{i,t-1}} + \beta_2 \mathbf{1}_{\text{Disruption}_{i,t}} + \beta_3 \mathbf{1}_{\text{Disruption}_{i,t}} \mathbf{1}_{\text{High}_{i,t-1}} + \varepsilon_{i,t}, \tag{20}$$

where the dependent variable $r_{i,t}$ is the return of firm i in quarter t, and $\mathbf{1}_{\text{Disruption}_{i,t}}$ is a dummy variable that takes a value of 1 if firm i experienced a supply chain disruption in quarter t. Furthermore, $\mathbf{1}_{\text{High}_{i,t-1}}$ indicates whether firm i was in the top quintile in terms of book-to-market (or investment) in quarter $t-1$. Effectively, we re-classify firms with respect to these characteristics every quarter, and study the link between their returns and disruptions in the next quarter. We are interested in the differential impact of disruptions on value vs. growth stocks; thus, we drop observations corresponding to quintiles 2-4.

Table 15 reports the result; the first 3 columns use any disruption, whereas columns (4)-(6) correspond to disruptions exceeding 1.7 percent of the recent firm-level import volume. Comparing column (1) with column (4), we see that supply chain disruptions are associated with a negative impact on realized returns, and the effect is nearly three times stronger in case of large disruptions. Importantly, supply chain disruptions affect value and low investment firms stronger than growth and high investment firms, respectively; the effect, however, is muted in case of all disruptions (the corresponding interaction coefficients have the expected sign but are statistically insignificant) but becomes pronounced in case of large disruptions. We see that, on average, supply chain disasters decrease returns of firms in the top quintile of book-to-market by 3.5pp more relative to stocks in the bottom quintile. At the same time, firms in the 5th quintile of the total asset growth have 3.4pp higher returns in the aftermath of a large disruption as compared with firms in the first quintile.

The presented evidence demonstrates that value firms are more exposed to supply chain disruptions (especially large ones) relative to growth firms. This offers additional empirical support to the central prediction of the model: a higher probability of microeconomic

Table 15: Supply Chain Disruptions and Realized Returns

	Any Disruption			Large Disruption		
	(1)	(2)	(3)	(4)	(5)	(6)
Disruption	-0.0067***	-0.0064***	-0.0095**	-0.0180***	-0.0104***	-0.0084
	(0.002)	(0.002)	(0.005)	(0.003)	(0.004)	(0.006)
High B/M		-0.0194***			-0.0168***	
		(0.003)			(0.003)	
High Inv			0.0110***			0.0082***
			(0.003)			(0.003)
High B/M x Disruption		-0.0088			-0.0348***	
		(0.006)			(0.008)	
High Inv x Disruption			0.0015			0.0342***
			(0.006)			(0.008)
Constant	0.0521***	0.0370***	0.0267***	0.0534***	0.0373***	0.0279***
	(0.006)	(0.007)	(0.008)	(0.006)	(0.007)	(0.008)
R^2	0.34	0.35	0.28	0.34	0.35	0.29
Observations	19545	19545	17252	19545	19545	17252

Notes: Table 15 reports results of OLS estimation of Equation (20). The dependent variable $r_{i,t}$ is the return of firm i in quarter t. In columns (1)-(3), `Disruption` is a dummy variable that takes a value of 1 if firm i experienced any supply chain disruption in quarter t; in columns (4)-(6) this dummy corresponds to disruptions exceeding 1.7 percent of recent import volume. Furthermore, `High B/M` and `High Inv` are also dummy variables and take a value of 1 if firm i was in the top quintile in terms of book-to-market or investment in quarter $t-1$, correspondingly. Investment is the growth in total assets from $t-4$ to $t-1$. Observations are value-weighted. Year-quarter fixed effects are included. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

disasters makes value firms more risky, thereby increasing their expected returns.

7 Conclusion

We developed a general equilibrium production-based asset pricing model which simultaneously accounts for the distribution of investment rates, business cycle statistics and asset pricing moments. One defining feature of the model is the presence of large, idiosyncratic negative shocks—microeconomic disasters. We highlighted the importance both of the size of these large shocks as well as of their persistence for aggregate and, especially, cross-sectional asset pricing implications. As an application of our model, we focused on supply chain disruptions. To this end, we utilized a large-scale shipment data on the universe of the seaborne

U.S. import and documented a dramatic increase in probability of very large supply chain disruptions over the last several years. The model, calibrated to account for this recent change, leads to 0.5pp and 0.4pp higher value and investment premiums, respectively.

References

Ai, Hengjie, Jun Li, and Jincheng Tong, "Equilibrium Value and Profitability Premiums," *manuscript*, 2021.

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

Bai, Hang, Erica Li, Chen Xue, and Lu Zhang, "Asymmetric Investment Rates," *manuscript*, 2022.

_ , Kewei Hou, Howard Kung, Erica Li, and Lu Zhang, "The CAPM strikes back? An Equilibrium Model with Disasters," *Journal of Financial Economics*, 2019, *131*, 269–298.

Beeler, Jason and John Campbell, "The Long-Run Risks Model and Aggregate Asset Prices: An Empirical Assessment," *Critical Finance Review*, 2012, *1*, 141–182.

Benigno, Gianluca, Julian di Giovanni, Jan Groen, and Adam Noble, "A New Barometer of Global Supply Chain Pressures," *Federal Reserve Bank of New York Staff Reports, no. 1017*, 2022.

Bouchaud, Jean-Philippe, Philipp Krueger, Augustin Landier, and David Thesmar, "Sticky Expectations and the Profitability Anomaly," *Journal of Finance*, 2019, *74*, 639–674.

Campbell, John and John Cochrane, "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior," *Journal of Political Economy*, 1999, *107*, 205–251.

Carvalho, Vasco, Makoto Nirei, Yukiko Saito, and Alireza Tahbaz-Salehi, "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake," *Quarterly Journal of Economics*, 2021, *136*, 1255–1321.

Chen, Andrew, "External Habit in a Production Economy: A Model of Asset Prices and Consumption Volatility Risk," *Review of Financial Studies*, 2017, *30*, 2890–2932.

_ , "A General Equilibrium Model of the Value Premium with Time-Varying Risk Premia," *Review of Asset Pricing Studies*, 2018, *8*, 337374.

Clementi, Gian Luca and Berardino Palazzo, "Entry, Exit, Firm Dynamics, and Aggregate Fluctuations," *American Economic Journal: Macroeconomics*, 2016, *8*, 1–41.

_ , Aubhik Khan, Berardino Palazzo, and Julia Thomas, "Entry, Exit and the Shape of Aggregate Fluctuations in a General Equilibrium Model with Capital Heterogeneity," *manuscript*, 2015.

Cohen, Lauren and Andrea Frazzini, "Economic Links and Predictable Returns," *Journal of Finance*, 2008, *63*, 1977–2011.

Cont, Rama and Peter Tankov, *Financial Modelling with Jump Processes*, Chapman and Hall, 2003.

Cooper, Russell and John Haltiwanger, "On the Nature of Capital Adjustment Costs," *Review of Economic Studies*, 2006, *73*, 611–633.

Davis, Steven, John Haltiwanger, and Scott Schuh, *Job Creation and Destruction*, MIT Press, 1996.

Dew-Becker, Ian, "Real-Time Forward-looking Skewness over the Business Cycle," *manuscript*, 2022.

Fama, Eugene and Kenneth French, "A Five-Factor Asset Pricing Model," *Journal of Financial Economics*, 2015, *116*, 1–22.

Flaaen, Aaron, Flora Haberkorn, Logan Lewis, Anderson Monken, Justin Pierce, Rosemary Rhodes, and Madeleine Yi, "Bill of Lading Data in International Trade Research with an Application to the COVID-19 Pandemic," *Finance and Economics Discussion Series 2021-066. Washington: Board of Governors of the Federal Reserve System*, 2021.

Guvenen, Fatih, Fatih Karahan, Serdar Ozkan, and Jae Song, "What Do Data on Millions of U.S. Workers Reveal about Life-Cycle Earnings Dynamics?," *Econometrica*, forthcoming.

Hendricks, Kevin and Vinod Singhal, "Association Between Supply Chain Glitches and Operating Perfomance," *Management Science*, 2005, *51*, 695–711.

Jain, Nitish and Di Wu, "Can Global Sourcing Strategy Predict Stock Returns?," *SSRN Working Paper 3606884*, 2020.

Jermann, Urban, "Asset Pricing in Production Economies," *Journal of Monetary Economics*, 1998, *41*, 257–275.

Kehrig, Matthias, "The Cyclical Nature of the Productivity Distribution," *SSRN Working Paper 1854401*, 2015.

Khan, Aubhik and Julia Thomas, "Idiosyncratic Shocks and the Role of Nonconvexities in Plant and Aggregate Investment Dynamics," *Econometrica*, 2008, *76*, 395–436.

_ and _ , "Credit Shocks and Aggregate Fluctuations in an Economy with Production Heterogeneity," *Journal of Political Economy*, 2013, *121*, 1055–1107.

_ , Tatsuro Senga, and Julia Thomas, "Default Risk and Aggregate Fluctuations in an Economy with Production Heterogeneity," *manuscript*, 2014.

Kogan, Leonid and Dimitris Papanikolaou, "Economic Activity of Firms and Asset Prices," *Annual Review of Fianancial Economics*, 2012, *4*, 361–384.

_ , Jun Li, and Harold Zhang, "Operating Hedge and Gross Profitability Premium," *manuscript*, 2022.

Krusell, Per and Anthony Smith, "Income and Wealth Heterogeneity in the Macroeconomy," *Journal of Political Economy*, 1998, *106*, 867–896.

Kwon, Caleb, "Supply Chain Disruptions: Evidence from the Bankruptcy of Hanjin Shipping," *manuscript*, 2021.

McKay, Alisdair and Ricardo Reis, "The Role of Automatic Stabilizers in the U.S. Business Cycle," *Econometrica*, 2016, *84*, 141–194.

McQuade, Timothy, "Stochastic Volatility and Asset Pricing Puzzles," *manuscript*, 2018.

Miranda, Mario and Paul Fackler, "Applied Computational Economics and Finance," *MIT Press*, 2002.

Novy-Marx, Robert, "The Other Side of Value: The Gross Profitability Premium," *Journal of Financial Economics*, 2013, *108*, 1–28.

Oh, Sangmin and Jessica Wachter, "Cross-Sectional Skewness," *Review of Asset Pricing Studies*, 2022, *12*, 155–198.

Reiter, Michael, "Solving Heterogeneous-Agent Models by Projection and Perturbation," *Journal of Economic Dynamics and Control*, 2009, *33*, 649–665.

Salgado, Sergio, Fatih Guvenen, and Nicholas Bloom, "Skewed Business Cycles," *manuscript*, 2020.

Schmidt, Lawrence, "Climbing and Falling Off the Ladder: Asset Pricing Implications of Labor Market Event Risk," *manuscript*, 2022.

Smirnyagin, Vladimir, "Returns to Scale, Firm Entry, and the Business Cycle," *SSRN working paper 3514855*, 2022.

Thomas, Julia, "Is Lumpy Investment Relevant for the Business Cycle?," *Journal of Political Economy*, 2002, *110*, 508–534.

Tsai, Jerry and Jessica Wachter, "Disaster Risk and Its Implications for Asset Pricing," *Annual Review of Financial Economics*, 2015, *7*, 219–252.

White House, "The Biden-Harris Plan to Revitalize American Manufacturing and Secure Critical Supply Chains 2022," 2022.

Winberry, Thomas, "A Method for Solving and Estimating Heterogeneous Agent Macro Models," *Quantitative Economics*, 2018, *9*, 1123–1151.

Yang, Alex, John Birge, and Rodney Parker, "The Supply Chain Effects of Bankruptcy," *Management Science*, 2015, *61*, 2320–2338.

Young, Eric, "Solving the Incomplete Markets Model with Aggregate Uncertainty Using the Krusell-Smith Algorithm and Non-Stochastic Simulations," *Journal of Economic Dynamics and Control*, 2010, *34*, 36–41.

Zhang, Lu, "The Value Premium," *Journal of Finance*, 2005, *60*, 67–103.

Zwick, Eric and James Mahon, "Tax Policy and Heterogeneous Investment Behavior," *American Economic Review*, 2017, *107*, 217–248.

Internet Appendix

"Macroeconomic and Asset Pricing Effects of Supply Chain Disasters"

by Vladimir Smirnyagin and Aleh Tsyvinski

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Appendix A: Empirical Appendix

This appendix provides further details for the empirical part of the paper, including data background, sample selection and additional empirical results referenced throughout the main text.

A.1 LBD

The Longitudinal Business Database (LBD) is the comprehensive panel dataset covering the universe of U.S. businesses and spanning the years 1976-2016. The unit of observation in the LBD is an establishment, which is defined as a single physical location where business operations take place. A firm is then defined as a set of establishments that are under common ownership or control.

The LBD is based on several sources, such as the Business Register (also known as the Standard Statistical Establishment Listing—SSEL), Economic Censuses, and surveys. The LBD offers the most reliable and complete data on births, deaths, and age of establishments operating in the US. There are several data issues potentially leading to measurement errors in identification of business formation (for example, non-administratively registered establishments may not be correctly identified, or gaps in the records of establishments). See Jarmin and Miranda (2002) and Chow et al. (2021) for more details on which efforts have been undertaken to mitigate these issues in the process of the LBD construction.

A.1.1 Identification of Birth and Death

The unit of observation in the LBD is an establishment, and variable `lbdnum`—which is robust to mergers and acquisitions—is used to track establishments over time.

Establishments The age of an establishment is measured as the number of years elapsed since the first year the establishment appeared in the data. Age cannot be measured for establishments born prior to 1976—the first year covered by the LBD. For that reason, in our empirical exercise we exclude the cohort of 1976.

Firms Identification of firm birth and death is associated with the construction of firm linkages over time. We follow a standard approach in the literature which is robust to ownership changes and acquisitions (Haltiwanger, Jarmin and Miranda, 2013). A new firm identifier emerges in the LBD either because a new firm is born or because an existing businesses undergoes a change of ownership and control (e.g., merger and acquisition, divestitures). We register a new firm when all of its establishments are of age 0. Accordingly, when a new firm identifier arises through a merger of two preexisting firms, it is not treated as a firm birth; rather, it is assigned the age of the oldest continuing establishment of the newly combined business. The firms are then allowed to age naturally regardless of mergers and acquisitions as long as the ownership and control do not change. A firm death occurs when a firm identifier disappears and all associated establishments cease operations and exit.

A.1.2 Employment

Establishments Employment (LBD variable `emp`) is defined as the number of full- and part-time employees as of March 12^{th}.[17]

Firms Firms can own a single establishment or many establishments, which may span multiple geographic areas and industries. Naturally, firm-level employment and payroll are calculated as the sum of employment and payroll across the establishments constituting that firm.

A.1.3 Industry

The LBD also includes detailed information on industry classification. The period of analysis covers the the transition from SIC to NAICS industry classification standards (which occurred in 1997), which leads to well-known classification issues. We, therefore, use a consistent NAICS 2012 industry classification variable `fk_naics12` constructed by Fort and Klimek (2016).

Firms are frequently comprised of establishments from several industries. For that reason, to each firm we assign an industry of its largest (in terms of employment) establishment on the year-by-year basis.

[17] This measure includes employees who are on paid sick leave, holidays, and vacations. The reported number also includes salaried officers and executives of corporations, but it excludes sole proprietors and partners of unincorporated businesses.

A.2 S&P Global Intelligence: Panjiva

A.2.1 Data Background

S&P Global Panjiva is the bill of lading dataset, which contains over a billion of shipment-level records of goods traded across borders. The data provide information on shippers (exporters), consignees (importers), product description, weight in metric tons, volume in TEUs (twenty-foot equivalent unit), and, in limited cases, estimated values of shipment transactions (in USD). Panjiva covers trade flows for the following countries: U.S., Brazil, Chile, Colombia, Ecuador, India, Sri Lanka, Mexico, Panama, Peru, Pakistan, Paraguay, Uruguay. For each of these countries, data users are able to observe both imports and exports of goods for all trading partners. In this paper, we work with U.S. imports, which amounts to nearly 200mln records spanning the time period from 2007 to the present time. With rare exceptions (e.g., Mexico), the data only covers seaborne imports and exports. U.S. import data are updated several times per week.

The raw data represents bills of lading (BoL) from U.S. Customs and Border Protection (CBP), which are freely available under the Freedom of Information Act of 1966 (FOIA). A BoL is a legal document that serves as a record that a shipment has been transported from its origin to its final destination. Each BoL requires companies to fill out various fields, including shipper/consignee name and address, description of the goods, vessel name, transport company name, ports of lading (loading) and unlading (unloading), weight, quantity, and container information.

Panjiva collects, parses and stores raw data in an accessible way. On top of the raw data, Panjiva also imputes several additional variable. The list of variables includes volume (imputed based on existing container information and other shipment characteristics), Harmonized System (HS) product codes (Panjiva applies text processing algorithms to assign HS codes to each shipment based on the verbal description of the shipment in the BoL), estimate of shipment value (in USD). The latter variable is based on publicly-available average unit values, and is currently unavailable for most transactions. Panjiva also includes a unique company ID variable that can be used to link transactions of consignees to their associated companies in other S&P datasets, such as Compustat.

A.2.2 Variables and Additional Features of the Data

Below we list some key variables available in U.S. import data sourced from Panjiva:

- `panjivarecordid` - unique shipment ID;
- `arrivaldate` - day of arrival;
- `conname` - consignee name;
- `shpname` - shipper name;
- `volumeteu` - volume of shipment in TEUs;
- `weightt` - weight of shipment in metric tons;

- `portoflading` - port where shipment was loaded on the vessel;
- `portofunlading` - U.S. port where shipment cleared customs;
- `vesselimo` - vessel identifier;
- `conpanjivaid` - consignee ID;
- `shppanjivaid` - shipper ID;
- `hscode` - 6-digit HS code;
- `companyid` - Capital IQ company ID.

Flaaen et al. (2021) provide a comprehensive analysis of key advantages and disadvantages of the Panjiva dataset, and find that these data accord well with administrate aggregate data on the containerized vessel import value (U.S. Census Bureau). There are, however, several limitations. First, the value of shipments is only available for about a half of records, which invalidates it for our analysis. Furthermore, firms may requests that the U.S. Customs and Border Protection (CBP) redact their identity in the shipper or consignee field; about 10 to 30 percent of records have missing `shppanjivaid` and/or `conpanjivaid` depending on the year.

According to Flaaen et al. (2021), after a firm requests redaction, this request is fulfilled for two years before requiring renewal. When a request expires, a firms transactions from that point forward are no longer redacted. These redaction requests must be made for a specific firm name, so firms that use multiple names on bills of lading must submit a request for each entity. Given that one feature Panjiva adds to the raw data is the matching of firm names (including likely typos) to a corporate entity, this can lead to firms having some but not all of their shipments represented in the database. We take this limitation into account when we construct our dataset.

A.2.3 Details on Sample Construction

We follow a sequence of steps to construct the final sample.

1. We start with the universe of shipments imported by U.S. consignees. We drop observations with the missing firm identifier, `conpanjivaid`.

2. Furthermore, we use the cross-reference file (also provided by Panjiva), and attempt to obtain `companyid`, the S&P identifier of firms, for each `conpanjivaid`. Not all consignees can be matched. According to the Panjiva representative: *"...there are many small private companies that are doing import/export around the world, and Panjiva will assign a unique Panjiva entity ID for all of them. But many times that entity may be too small for Capital IQ to cover, simply because there is no other information about that company in order to initiate coverage."* Observations with the missing `companyid` are dropped from the sample.

3. Panjiva provides a concordance file, where each `companyid` is associated with the `ultimateparentcompanyid`. We obtain IDs of the ultimate parent for each firm in the sample, and drop those for which this ID is missing (very few observations get dropped at this stage).

4. We next attempt to obtain `gvkey`, the firm identifier in Compustat, based on the ID of the ultimate parent. For this purpose, we use the crosswalk which we download from WRDS.[18] The crosswalk contains the starting and ending date for every `companyid-gvkey` tuple; we make sure to use the correct concordance depending on the time period. That is, for each year, we keep those tuples which are active in a given year, and apply the restricted crosswalk to our sample.

5. We drop observations with the missing shipper identity, `shppanjivaid`.

6. Provided that our focus is on firms which actively trade, we drop firms if we observe them making transactions less than 50 percent of the time. About 15 percent of observations are dropped at this step.

7. As we mentioned in Section A.2.2, firms may redact their identities (or identities of shippers). We attempt to reduce the impact of this limitation by dropping firms if the number of unique shippers exceeds the mean plus/minus 3 standard deviations at any point of time. The mean and standard deviation are computed individually for each firm. This way, we try to get rid of companies which have big spikes (up or down) in the number of shippers; this can (plausibly) result from their redacting activity.

A.2.4 Largest U.S. Consignees

Figure C9 plots the top-10 public U.S. consignees by total volume imported (in TEUs), and shows how their importing activity has been evolving over time. Interestingly, these firms appear to be stable during the Great Recession in terms of imported volume; however, most of them exhibit a substantial decline in imports in the last several years. Figure C10 demonstrates that these largest firms tend to have hundreds of unique foreign shippers, sometimes this number exceeds 400.

[18] https://wrds-www.wharton.upenn.edu/pages/get-data/compustat-capital-iq-standard-poors/capital-iq/identifiers/.

A.3 Alternative Definitions of Supply Chain Disruptions

As we have discussed in Section 6.2, according to the baseline definition, a supply chain disruption between consignee i and shipper j in quarter t has to satisfy the following 3 criteria:

1. trade pair was active in each of the preceding 4 quarters;
2. trade pair was inactive in t;
3. there was at least one transaction between i and j in $t+1$.

For simplicity, let us refer to this definition as a "4-0-1" rule. The first digit refers to the number of (consecutive) quarters before t that the trade pair has to be active, the middle number denotes that the pair does not trade at t, and the last digit means the number of (consecutive) quarters after t that the pair has to be active.

We considered the following 5 alternative definitions: "6-0-1", "2-0-1", "4-0-2", "4-0-0", and "4-0-3/4". First of all, we found that the requirement of observing trade pair activity for 4 quarters before t is important; as in evident from Table D14, there is no statistically significant relationship between sales growth and disruptions defined according to the "2-0-1" rule. This is also not surprising provided that the time-series of the share of disrupted trade pairs is much less volatile (see Figure C12). Furthermore, one cannot ignore attrition considerations (see Section 6.2 for discussion); in particular, there is no link between sales growth and disruptions in case of the "4-0-0" rule (Table D16).

The remaining rules ("6-0-1", "4-0-2", and "4-0-3/4") deliver qualitatively similar to the baseline results, which, however, are quantitatively stronger (see Tables D13, D15 and D17). This is something one could expect provided that these definitions are more likely to capture disruptions to major, long-lasting trade relationships. They, however, place more stringent requirements on the data, and reduce both the number of identified supply chain disruptions and the number of periods when it is feasible to identify those disruptions. The baseline rule strikes a balance between the aforementioned limitations.

A.4 Supply Chain Disruptions and Realized Returns in 2020

The model predicts that an increase in supply chain disruptions leads to disproportionately higher expected returns of value stocks. To test this in the data, in this appendix we chose to focus on the episode with a dramatic increase in supply chain disruptions in the first quarter of 2020. We sort firms into two categories (above and below the median) with respect to their book-to-market ratio in 2019q4, and subsequently evaluate whether supply chain disruptions are associated with a bigger decline in realized returns for high B/M firms relative to low B/M stocks. We repeat the same exercise by splitting firms with respect to growth in their total assets. We estimate the following model:

$$r_{i,2020q1} = \beta_0 + \beta_1 \mathbf{1}_{\text{Above P50}_{i,2019q4}} + \beta_2 \mathbf{1}_{\text{Disruption}_{i,2020q1}} + \\ + \beta_3 \mathbf{1}_{\text{Disruption}_{i,2020q1}} \mathbf{1}_{\text{Above P50}_{i,2019q4}} + \varepsilon_i. \quad \text{(A.1)}$$

The dependent variable $r_{i,2020q1}$ in Equation (20) is the return of firm i in quarter 2020q1. $\mathbf{1}_{\text{Disruption}}$ is a dummy variable that takes a value of 1 if firm i experienced any supply chain disruption in quarter 2020q1. Furthermore, $\mathbf{1}_{\text{Above P50}}$ indicates whether the firm was above the median in terms of book-to-market (or investment) in quarter 2019q4.

Table A1: Supply Chain Disruptions and Realized Returns

	$r_{i,2020q1}$	
	(1)	(2)
Disruption	0.0094	-0.0684***
	(0.015)	(0.018)
High B/M	-0.1691***	
	(0.014)	
High Inv		0.0673***
		(0.013)
High B/M x Disruption	-0.0557**	
	(0.027)	
High Inv x Disruption		0.1250***
		(0.026)
Constant	-0.1536***	-0.2316***
	(0.007)	(0.010)
R^2	0.22	0.10
Observations	857	857

Notes: Table A1 reports results of OLS estimation of Equation (A.1). The dependent variable $r_{i,2020q1}$ is the return of firm i in quarter 2020q1. `Disruption` is a dummy variable, which takes a value of 1 if firm i experienced any supply chain disruption in quarter 2020q1. Furthermore, `High B/M` and `High Inv` are also dummy variables and take a value of 1 if firm i was above the median in terms of book-to-market or investment in quarter 2019q4, correspondingly. Investment is equal to $(\texttt{atq}_{i,2019q4} - \texttt{atq}_{i,2019q1})/\texttt{atq}_{i,2019q1}$, where `atq` is firm's total assets. Observations are value-weighted. *, **, and *** denote significance at the 10 percent, 5 percent, and 1 percent level, respectively.

Table A1 reports the result; the first column sorts firms with respect to book-to-market in 2019q4, the second column splits them with respect to asset growth. In both specifications, the constant is negative and highly significant, reflecting an overall poor performance of the stock market in the first quarter of 2020. High book-to-market stocks and low investment firms had lower returns in 2020q1 (conditional on no disruptions); this is indicative of higher exposure of these firms to the adverse aggregate shock.

Critically, however, supply chain disruptions had a much bigger impact on value and low investment stocks. In particular, we find that supply chain disruptions were associated with a 6pp (13pp) bigger decline in quarterly realized returns on value (low investment) firms relative to growth (high investment) firms. Thus, the data provide support for the model's prediction in that unproductive firms are more exposed to supply chain disruptions, and, thus earn higher expected returns.

Appendix B: Model Appendix

The computation of the model can be broadly divided into three parts: (1) simplification of programming problems by way of combining household's and firms' optimization problems, (2) computation of the model at the steady-state, and (3) solving for the equilibrium of the model with aggregate fluctuations using perturbation techniques. In what follows, we lay out the key details of the numerical algorithm. We start with a formal definition of the recursive competitive equilibrium for the model outlined in Section 3.

B.1 Definition of Equilibrium

The Recursive competitive equilibrium for this economy consists of the following functions:

$$\left\{v, v^{\text{adj}}, v^{\text{no adj}}, n, k', W, \widehat{\eta}, \omega_0, \omega_1, H, C, \Xi, M\right\},$$

such that:

1. H solves the household's problem (13)—(14), and (C, Ξ) are the associated policy functions,

2. $v, v^{\text{adj}}, v^{\text{no adj}}$ solve the firm's problem, and (k', n) are the corresponding policy functions,

3. consistency condition satisfies $\forall (k, z) \in \mathcal{K} \times \mathcal{Z}$
$$\Xi(k', z'; \mathbf{S}) = \mu'(k', z'),$$

4. threshold value $\widehat{\eta}$ arises from the associated programming problem (9),

5. labor market clears
$$1 = N(\mathbf{S}) = \int n(k, z; \mathbf{S}) \mathrm{d}\mu + \int \frac{\widehat{\eta}(k, z; \mathbf{S})^2}{2\bar{\eta}} \mathrm{d}\mu,$$

6. stochastic discount factor satisfies
$$M(\mathbf{S}, \mathbf{S}') = \beta \frac{U_C'(C(\mathbf{S}') \times S')}{U_C'(C(\mathbf{S}) \times S)},$$

7. goods market clears
$$C(\mathbf{S}) = Y(\mathbf{S}) - I(\mathbf{S}) - AC(\mathbf{S}),$$

where

$$
\begin{aligned}
Y(\mathbf{S}) &= \int e^{X^Z} e^z k^\theta n^\nu \mathrm{d}\mu, \\
I(\mathbf{S}) &= \int \left\{ \left(\frac{\widehat{\eta}(k,z;\mathbf{S})}{\bar{\eta}} \right) k'(k,z;\mathbf{S}) + \left(1 - \frac{\widehat{\eta}(k,z;\mathbf{S})}{\bar{\eta}} \right) \bar{k}'(k,z;\mathbf{S}) - (1-\delta)k \right\} \mathrm{d}\mu, \\
AC(\mathbf{S}) &= \int AC(k'(k,z;\mathbf{S}), k)\mathrm{d}\mu,
\end{aligned}
$$

where $\bar{k}'(k,z;\mathbf{S}) = \min\{(1-\delta+b)k, \max\{(1-\delta-b)k, k'(k,z;\mathbf{S})\}\}$.

8. law of motion for the aggregate state vector $\Gamma(\cdot)$ is consistent with firms' policy functions.

B.2 Analysis of the Model

The model outlined in Section 3 incorporates optimization problems for a representative household and heterogeneous firms. This implies that, first, we need to solve two programming problems, and then make sure that the agents' decisions are consistent with each other and that markets clear. Fortunately, it is possible to combine the optimality conditions for the household's and firms' Bellman equations, and thereby reduce the computational complexity of the problem at hand. Using $C(\mathbf{S})$ to denote the market clearing value of household consumption, it is straightforward to show that market-clearing requires firms' state-contingent discount factor to be consistent with the household marginal rate of substitution over time:

$$M(\mathbf{S}, \mathbf{S}') = \beta \frac{U_1'(C(\mathbf{S}') \times S')}{U_1'(C(\mathbf{S}) \times S)}.$$

Following Khan and Thomas (2008), we compute for the recursive competitive equilibrium effectively substituting the equilibrium implications of household optimization into the recursive problems faced by the firms. This means that we scale all value functions by $p(\mathbf{S})$—the marginal utility of the household with respect to equilibrium consumption $C(\mathbf{S})$.

Next, we lay out the algorithm which we used to solve for the equilibrium.

B.3 Steady-State

We use collocation methods to solve the firm's functional equations. In practice, we use Chebyshev polynomials to approximate value functions.

We set up a grid of collocation nodes $\mathcal{K} \times \mathcal{Z}$, with N_i nodes in each dimension, $i \in \{\mathcal{K}, \mathcal{Z}\}$. The computation of the stationary state of the model proceeds in the following 4 steps:

1. guess the equilibrium wage rate, W;

2. solve for individual decision rules k';

3. given the decision rules, compute stationary histogram (distribution of firms over the state space);

4. compute the excess demand on the labor market. If it exceeds some prespecified tolerance, adjust the wage guess correspondingly and go back to Step 2. Otherwise, terminate.

B.3.1 Approximation of Value Functions

We approximate four (normalized by the household's marginal utility) value functions: $V^e(\cdot), V^{\text{cont}}(\cdot)$, $V^{\text{adj}}(\cdot)$ and $V^{\text{no adj}}(\cdot)$. We represent these value functions as weighted sums of orthogonal polynomials:

$$\begin{cases} V^e(k,z) & = \sum_{a,b=1,1}^{N_{\mathcal{K}}N_{\mathcal{Z}}} \theta_0^{ab} T^a(k) T^b(z) \\ V^{\text{cont}}(k,z) & = \sum_{a,b=1,1}^{N_{\mathcal{K}},N_{\mathcal{Z}}} \theta_1^{ab} T^a(k) T^b(z) \\ V^{\text{adj}}(k,z) & = \sum_{a,b=1,1}^{N_{\mathcal{K}},N_{\mathcal{Z}}} \theta_2^{ab} T^a(k) T^b(z) \\ V^{\text{no adj}}(k,z) & = \sum_{a,b=1,1}^{N_{\mathcal{K}},N_{\mathcal{Z}}} \theta_3^{ab} T^a(k) T^b(z) \end{cases}$$

where $\mathbf{\Theta} = \{\theta_0^{a,b}, \theta_1^{a,b}, \theta_2^{a,b}, \theta_3^{a,b}\}$ are approximation coefficients, and $T^i(\cdot)$ is the Chebyshev polynomial of order i.

We use a collocation method to simultaneously solve for $\mathbf{\Theta}$. Collocation method requires setting the residual equation to hold exactly at $N = N_{\mathcal{K}} \times N_{\mathcal{Z}}$ points ; therefore, we essentially solve for $4 \times N$ unknown coefficients. We compute the basis matrices for Chebyshev polynomials using Miranda and Fackler (2002) Compecon toolbox. Subsequently, we solve for a vector of unknown coefficients using Newton's method. A much slower alternative is to iterate on the value function. Given the current guess of coefficients, we solve for the optimal policy $k'(k,z)$ using vectorized golden search. After we solve for the policy function, we recompute decision rules on a finer grid, and, subsequently, compute the stationary distribution.

B.3.2 Stationary Distribution

When we solve for a stationary distribution, we iterate on a mapping using firms' decisions rules:

$$L' = \mathbf{Q}' L,$$

where L is a current distribution of firms across the state space. Matrix $\mathbf{Q}$ is a transition matrix, which determines how mass of firms shifts in the (k,z)-space. It is a direct product of three transition matrices $\mathbf{Q}_k$, and $\mathbf{Q}_z$:

$$\mathbf{Q} = \mathbf{Q}_k \odot \mathbf{Q}_z,$$

which govern the shift of mass along k- and z-dimensions, respectively. While $\mathbf{Q}_z$ is completely determined by the exogenous stochastic process, matrix $\mathbf{Q}_k$ is constructed so that the model generates an unbiased distribution in terms of aggregates.[19] More precisely, element (i,j) of the transition matrix $\mathbf{Q}_k$ informs which fraction of firms with the current idiosyncratic state k_i will end up having k_j tomorrow. Therefore, this entry of the matrix is

[19] See Young (2010) for more details.

computed as:

$$\mathbf{Q}_k(i,j) = \left[\mathbf{1}_{k' \in [k_{j-1}, k_j]} \frac{k' - k_j}{k_j - k_{j-1}} + \mathbf{1}_{k' \in [k_j, k_{j+1}]} \frac{k_{j+1} - k'}{k_{j+1} - k_j}\right].$$

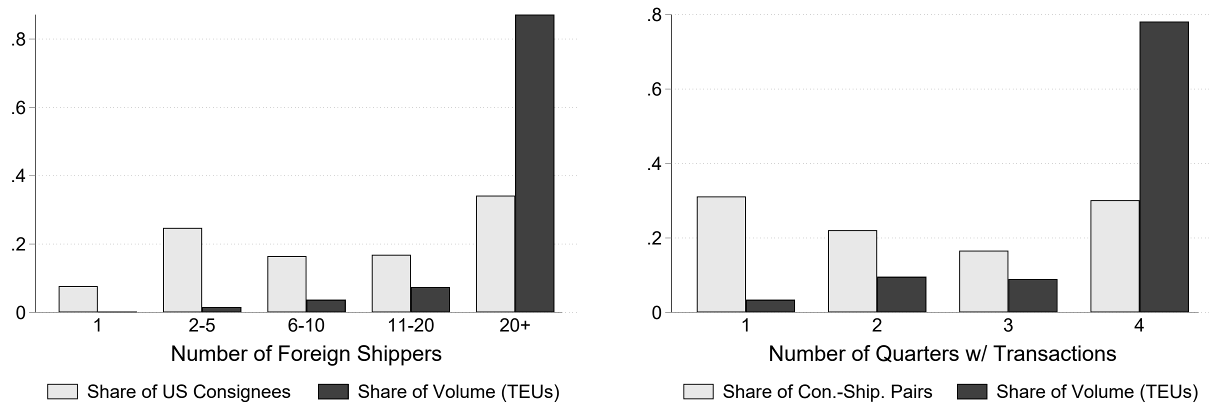
Tensor product of matrices $\mathbf{Q}_k$ and $\mathbf{Q}_z$ is computed using the `dprod` function from the Miranda and Fackler (2002) toolkit.

B.4 Model with Aggregate Shocks

We solve the model with aggregate uncertainty using the second-order perturbation around the non-stochastic steady-state in Dynare following the steps outlined in Winberry (2018). Provided that the model features rare large drops in productivity, we chose to keep track of the fine histogram instead of using a parametric family to approximate the distribution.

Appendix C: Additional Figures

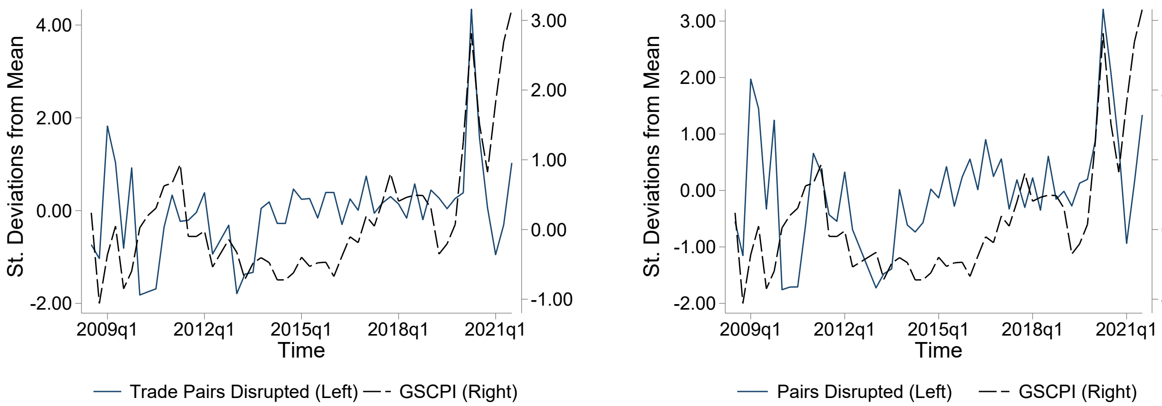
Figure C1: Characteristics of Seaborne Import by U.S. Public Firms



(A) Distribution of firms by num. of shippers (B) Frequency of transactions by trade pair

Notes: Figure C1 consists of two panels. Panel (A) plots the distribution of U.S. public firms (consignees) by the number of foreign shippers (gray bars) in 2019. Panel (B) plots the distribution of trade pairs with respect to transaction frequency in 2019; the sample is restricted to those pairs which traded at least once in 2018. Black bars show shares of total import by volume (TEUs) that each category accounts for.

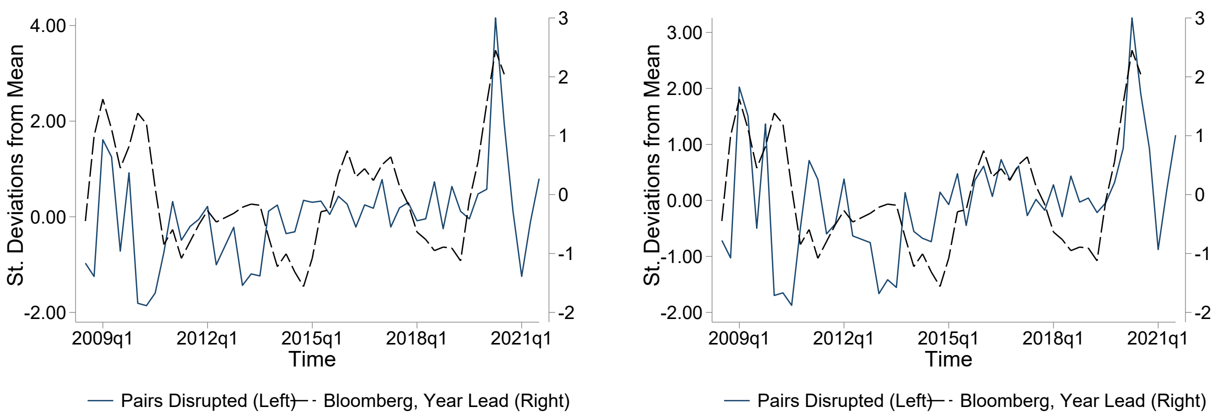
Figure C2: Share of Disrupted Trade Pairs vs. GSCPI



(A) Full sample (B) Compustat sample

Notes: Figure C2 consists of 2 panels. Panel (A) compares the share of disrupted trade pairs computed according to the definition provided in Section 6.2 against the Global Supply Chain Pressure Index (GSCPI). See Appendix A.2.3 for details on sample construction. Panel (B) plots same object for the Compustat subsample. All series are represented in terms of standard deviations from the time-series average.

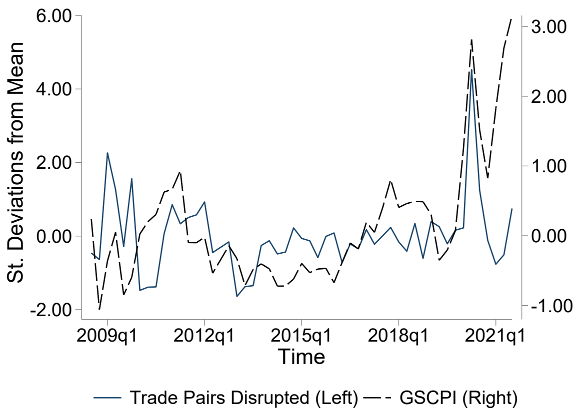
Figure C3: Share of Disrupted Trade Pairs vs. Bloomberg Index



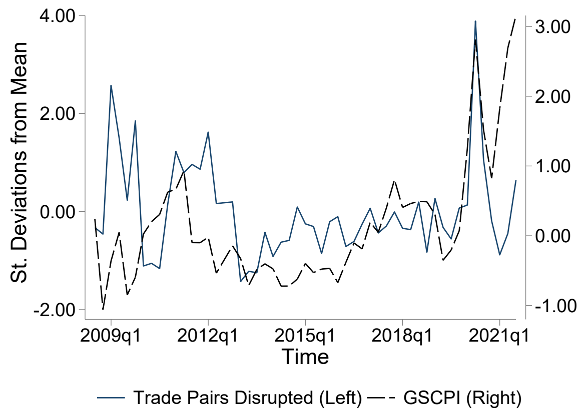
(A) Full sample (B) Compustat sample

Notes: Figure C3 consists of 2 panels. Panel (A) plots the shares of trade pairs being disrupted by quarter according to the definition provided in Section 6.2 against the one year lead of the Bloomberg Supply Constraints Indicator. Both series are represented in terms of standard deviations from the time-series average. Panel (B) repeats the exercise for the Compustat subsample. Datasource: S&P Global Market Intelligence and Bloomberg.

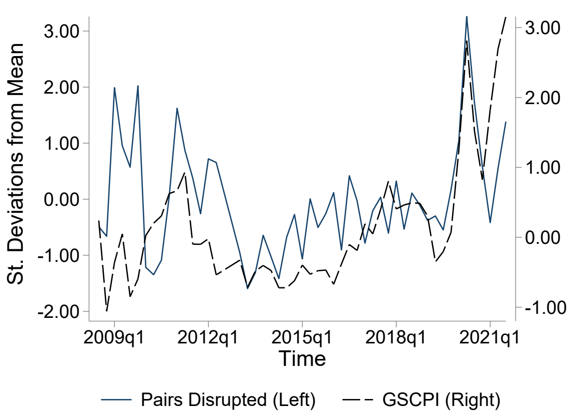
Figure C4: Share of Disrupted Trade Pairs by Importance to Firms vs. GSCPI



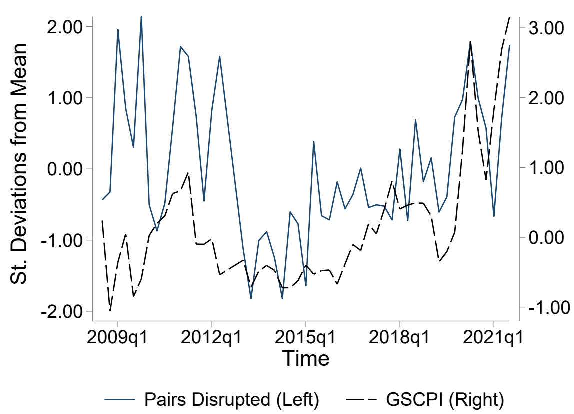
(A) Disruptions ($\geq 0.5\%$), full



(B) Disruptions ($\geq 1.7\%$), full



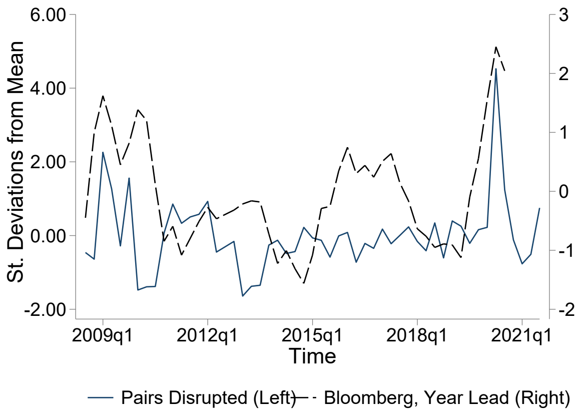
(C) Disruptions ($\geq 0.5\%$), Compustat



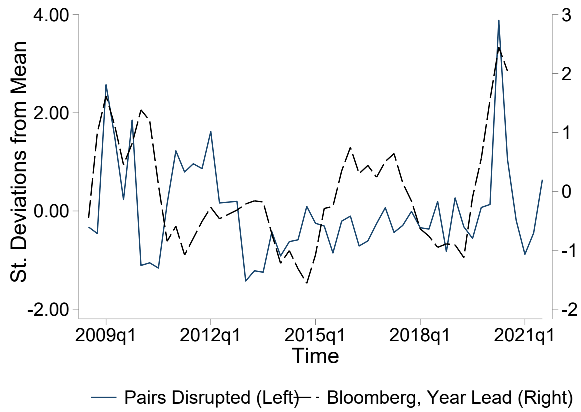
(D) Disruptions ($\geq 1.7\%$), Compustat

Notes: Figure C4 consists of 4 panels. Panels (A) and (C) plot shares of pairs being disrupted by quarter according to the definition provided in Section 6.2 for the full sample and public firms subsample, correspondingly; disrupted trade pairs that account for at least 0.5 percent of the firm-level import volume over the last 4 quarters are considered. See Appendix A.2.3 for details on sample construction. Panels (B) and (D) plot probability of disruptions that account for at least 1.7% ($= 0.5\% + 3 \times 0.4\%$) of firm-level import volume for the full sample and public firms subsample, correspondingly. Both series are represented in standard deviations from the time-series average, and are plotted against the FRB NY Global Supply Chain Pressure index.

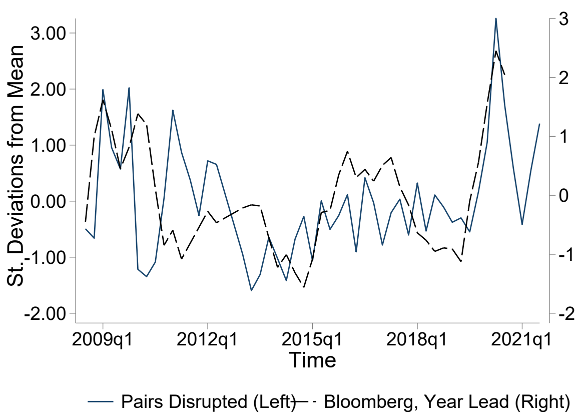
Figure C5: Share of Disrupted Trade Pairs by Importance to Firms vs. Bloomberg Index



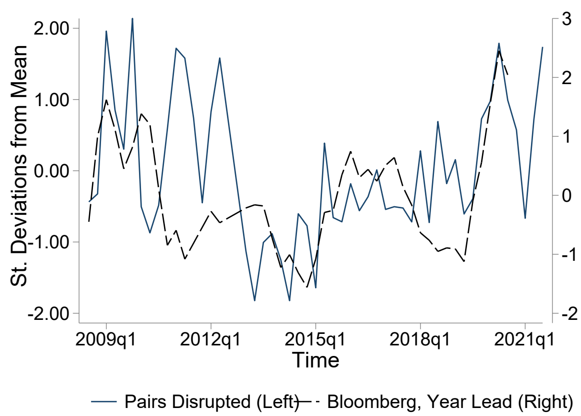
(A) Disruptions ($\geq 0.5\%$), full



(B) Disruptions ($\geq 1.7\%$), full



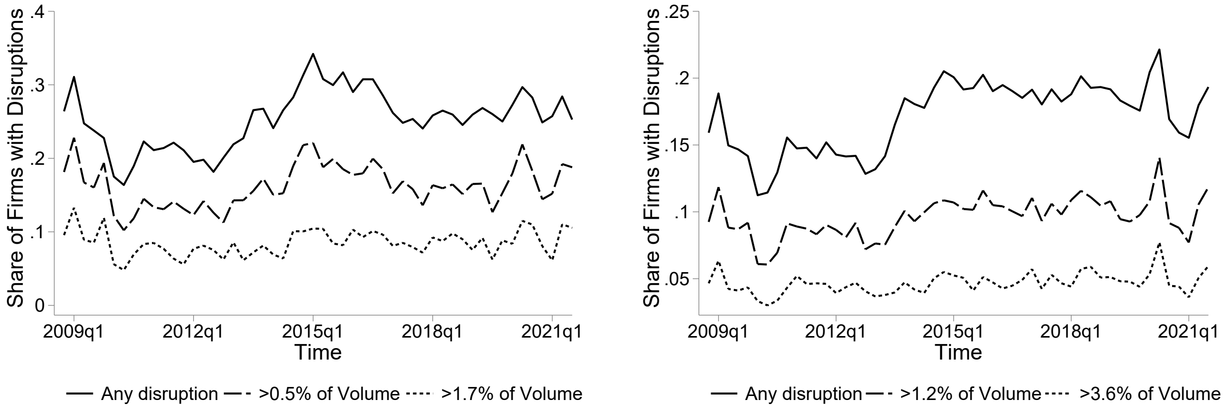
(C) Disruptions ($\geq 0.5\%$), Compustat



(D) Disruptions ($\geq 1.7\%$), Compustat

Notes: Figure C5 consists of 4 panels. Panels (A) and (C) plot shares of pairs being disrupted by quarter according to the definition provided in Section 6.2 for the full sample and public firms subsample, correspondingly; disrupted trade pairs that account for at least 0.5 percent of the firm-level import volume over the last 4 quarters are considered. See Appendix A.2.3 for details on sample construction. Panels (B) and (D) plot probability of disruptions that account for at least 1.7% ($= 0.5\% + 3 \times 0.4\%$) of firm-level import volume for the full sample and public firms subsample, correspondingly. Both series are represented in standard deviations from the time-series average, and are plotted against the one year lead of the Bloomberg Supply Constraints Indicator.

Figure C6: Share of Firms Experiencing a Disruption

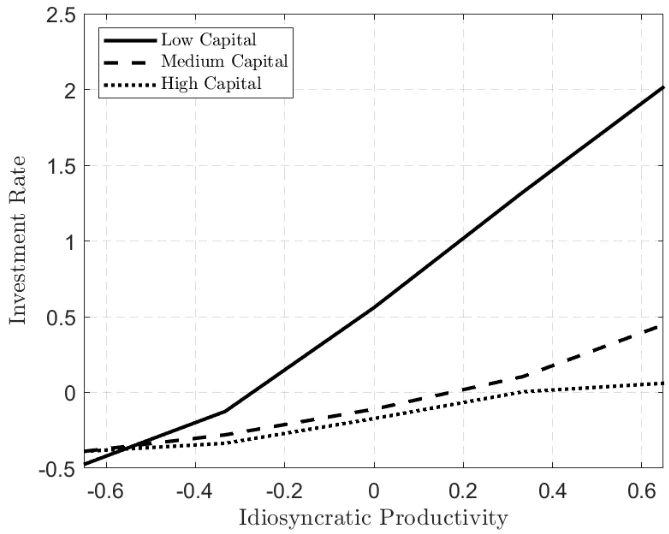


(A) Compustat sample

(B) Full sample

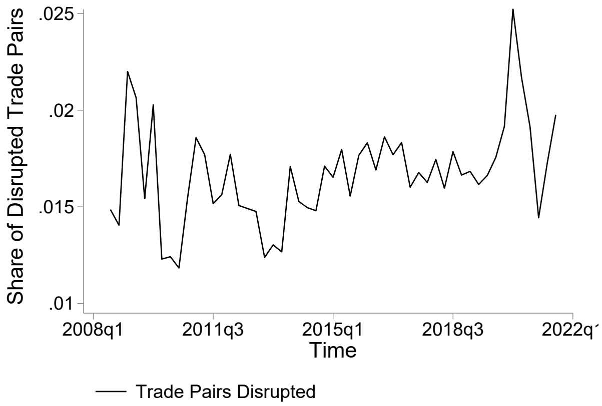
Notes: Figure C6 contains two panels, each panel has three lines. The solid line plots the share of firms in our sample that experience any disruption. The dashed line corresponds to the share of firms that experience disruption(s) that cumulatively account for at least 0.5 percent (1.2 percent) of the firm-level trade volume over the preceding 4 quarters. The dotted line does the same but for disruptions exceeding 1.5 percent (3.6 percent) of total import volume. Panel (A) corresponds to the sample of public firms, panel (B) corresponds to the full sample. Both samples are limited to firms with at least 20 shippers (on average).

Figure C7: Investment Rate and Idiosyncratic Productivity

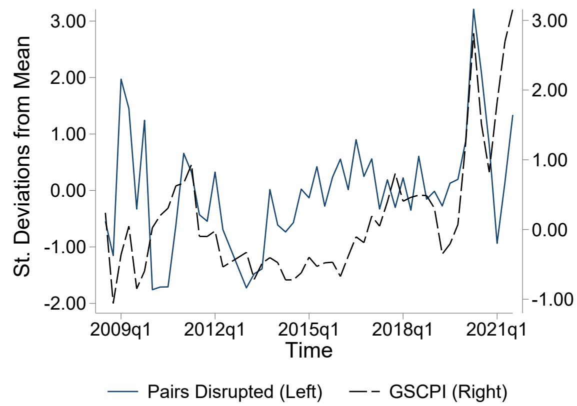


Notes: Figure C7 plots investment rate against idiosyncratic productivity in the steady state. Solid, dashed and dotted lines correspond to low, medium and high levels of idiosyncratic capital, respectively.

Figure C8: Share of Disrupted Trade Pairs, U.S. Public Firms



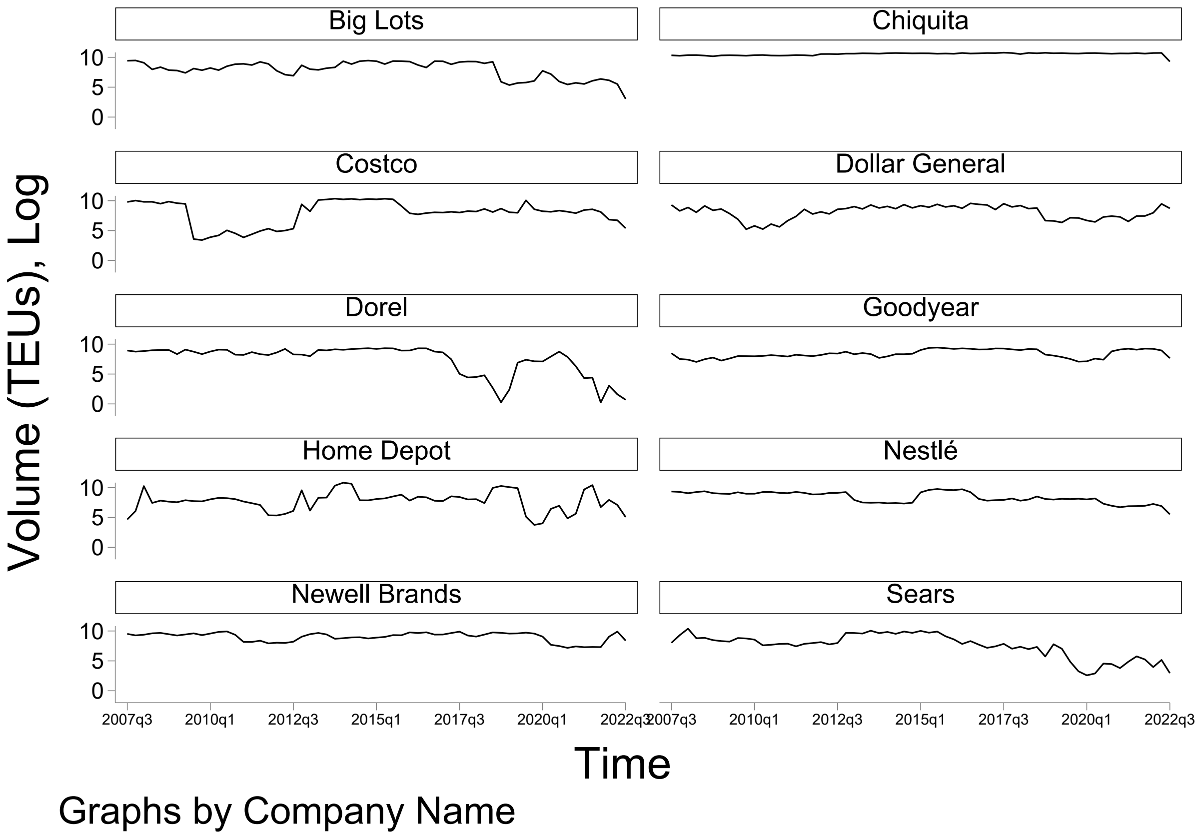
(A) Share of trade pairs disrupted



(B) Comparison against GSCP index

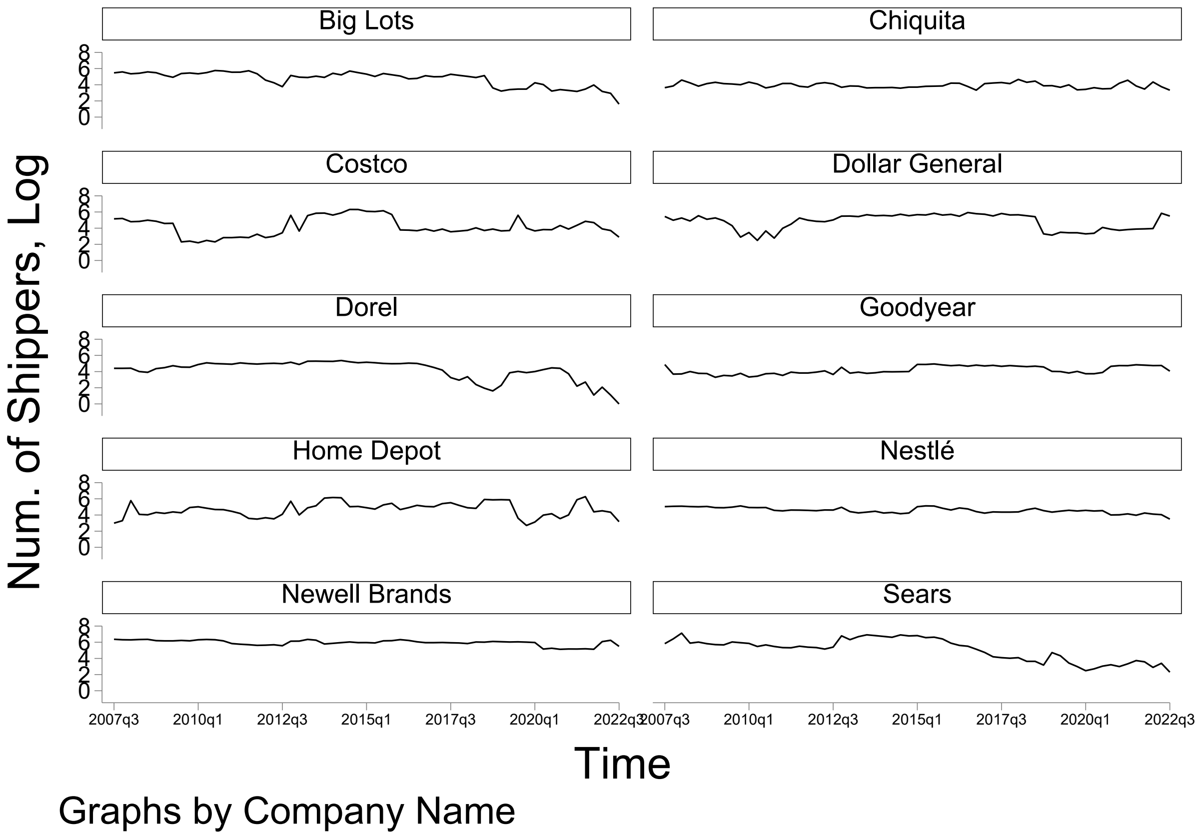
Notes: Figure C8 consists of 2 panels. Panel (A) plots the shares of trade pairs being disrupted by quarter according to the definition provided in Section 6.2. The underlying sample consists of a subset of U.S. public firms. See Appendix A.2.3 for details on sample construction. Panel (B) compares that series against the FRB NY Global Supply Chain Pressure index. Both series are represented in terms of standard deviations from the time-series average.

Figure C9: Top 10 U.S. Consignees, Total Volume



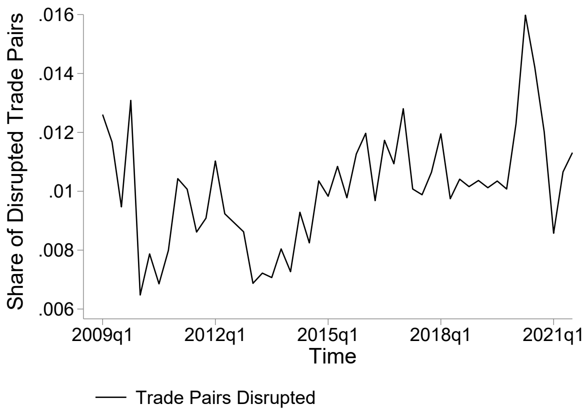
Notes: Figure C9 plots the total volume imported (in TEUs) for the top 10 largest U.S. consignees in the Compustat sample.

Figure C10: Top 10 U.S. Consignees, Number of Shippers

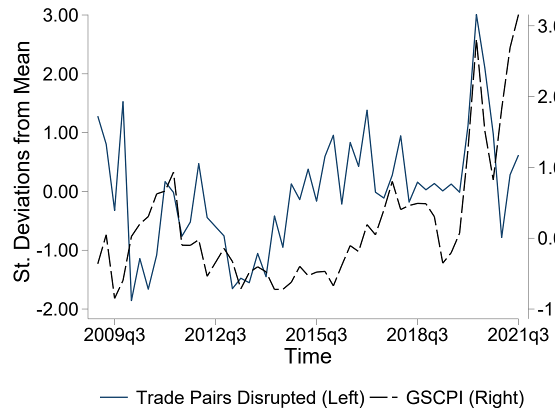


Notes: Figure C10 plots the number of shippers for the top 10 largest U.S. consignees in the Compustat sample.

Figure C11: Share of Disrupted Trade Pairs, "6-0-1" Rule



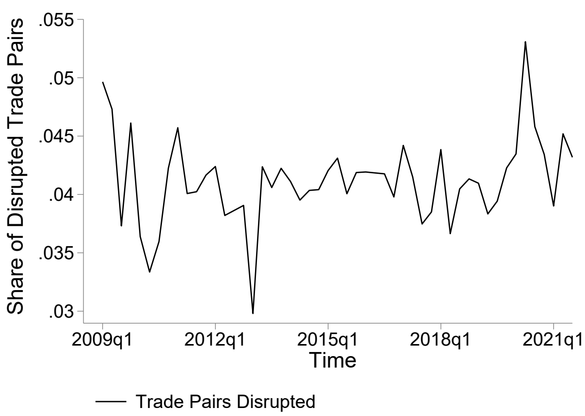
(A) Share of trade pairs disrupted



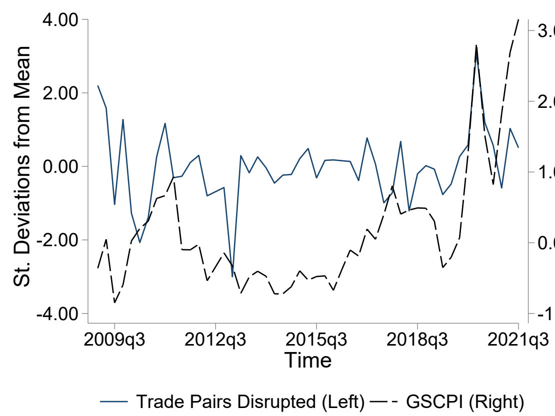
(B) Comparison against GSCP index

Notes: See notes for Figure 7.

Figure C12: Share of Disrupted Trade Pairs, "2-0-1" Rule



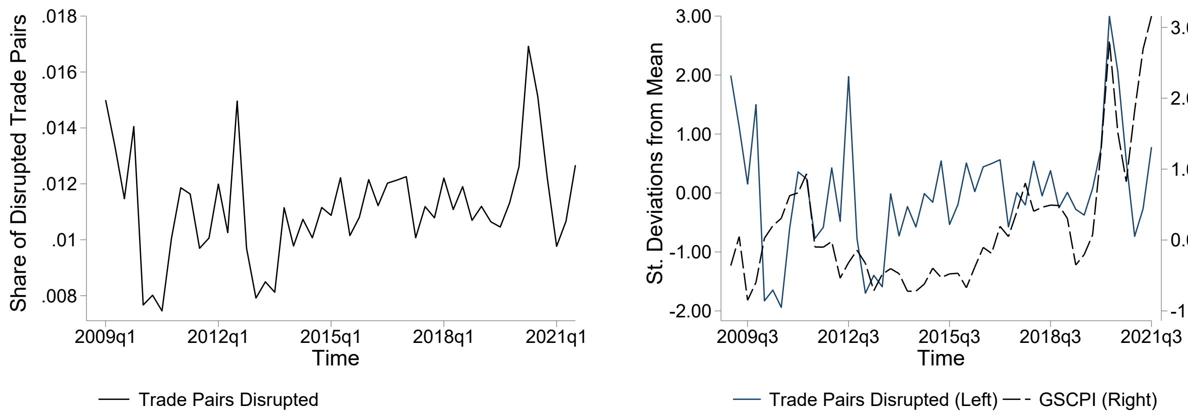
(A) Share of trade pairs disrupted



(B) Comparison against GSCP index

Notes: See notes for Figure 7.

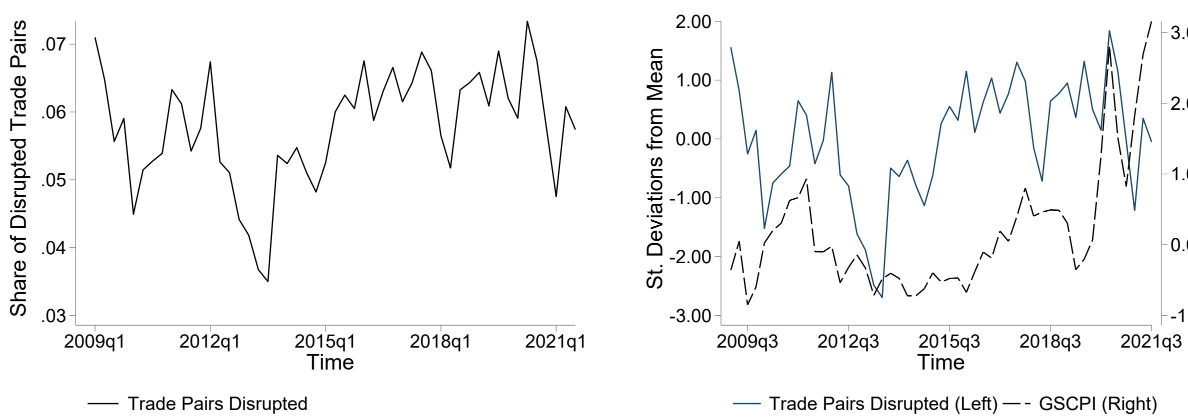
Figure C13: Share of Disrupted Trade Pairs, "4-0-2" Rule



(A) Share of trade pairs disrupted (B) Comparison against GSCP index

Notes: See notes for Figure 7.

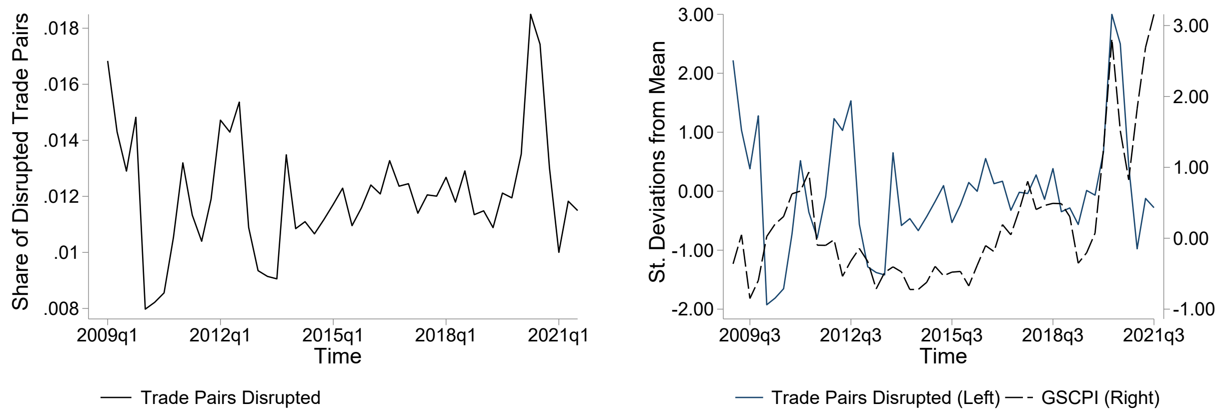
Figure C14: Share of Disrupted Trade Pairs, "4-0-0" Rule



(A) Share of trade pairs disrupted (B) Comparison against GSCP index

Notes: See notes for Figure 7.

Figure C15: Share of Disrupted Trade Pairs, "4-0-3/4" Rule

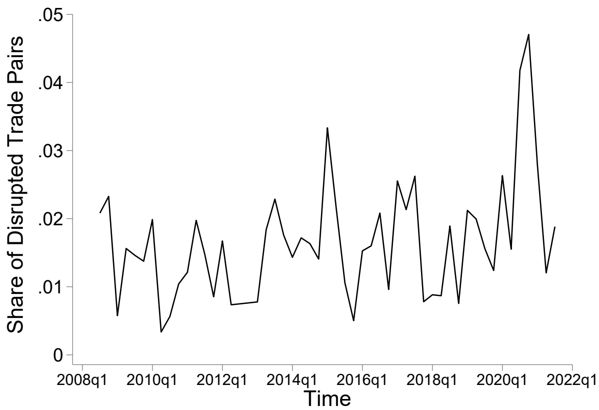


(A) Share of trade pairs disrupted

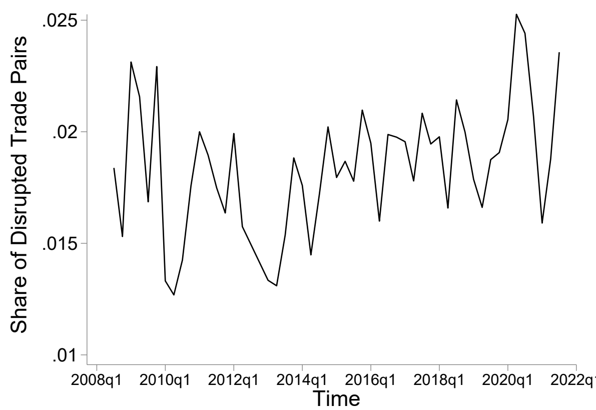
(B) Comparison against GSCP index

Notes: See notes for Figure 7.

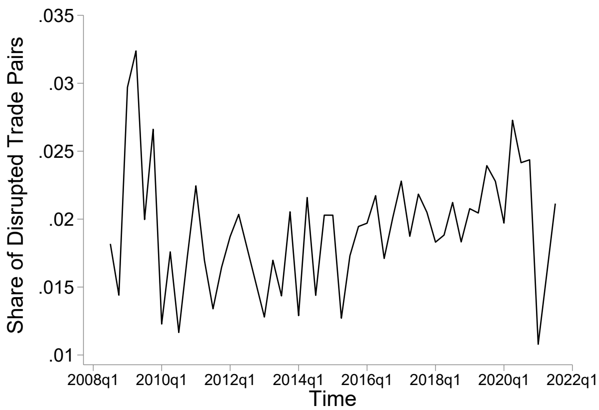
Figure C16: Share of Disrupted Trade Pairs for Selected NAICS 2-digit Industries



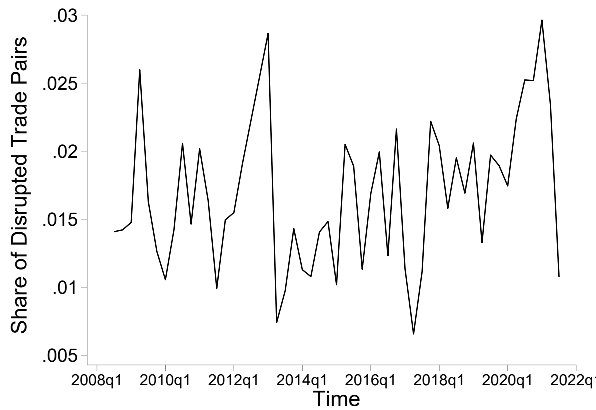
(a) Mining



(b) Manufacturing



(c) Wholesale



(d) Information

Notes: Figure C16 plots shares of trade pairs being disrupted by NAICS 2-digit industry. The underlying sample covers a subset of publicly traded firms, see Appendix A.2.3 for details on sample construction.

Appendix D: Additional Tables

Table D1: Summary Statistics, 2009

Full Sample						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	2895	0.488	1.198	0.016	0.206	1.029
Volume (1000s TEUs)	2895	1.170	5.970	0.012	0.253	2.207
Number of shippers	2895	61.6	77.8	6.0	42.0	126.0
Share redacted	2895	0.009	0.024	0.000	0.001	0.023
Number of disruptions	2895	0.461	0.728	0.000	0.250	1.250
Share of import disrupted	2479	0.020	0.047	0.000	0.007	0.047
Compustat						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	397	1.044	1.776	0.090	0.410	2.541
Volume (1000s TEUs)	397	2.610	7.705	0.076	0.651	6.365
Number of shippers	397	112.4	129.6	21.0	63.0	270.0
Share redacted	397	0.007	0.012	0.000	0.003	0.019
Sales(bn)	402	13.49	31.53	0.27	2.85	34.04
Total assets(bn)	397	35.02	182.18	0.26	2.66	47.58
Quarterly sales growth	386	0.005	0.082	-0.064	0.003	0.065
Number of disruptions	402	0.679	1.342	0.000	0.000	2.250
Share of import disrupted	402	0.006	0.012	0.000	0.000	0.022

Notes: Table D1 reports summary statistics for the underlying sample of U.S. firms for year 2009. Nominal variables have been converted to real ones using the Producer Price Index with 2015 being the base year.

Table D2: Summary Statistics, 2010

Full Sample						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	2913	0.529	1.431	0.016	0.224	1.068
Volume (1000s TEUs)	2913	1.256	6.191	0.013	0.275	2.326
Number of shippers	2913	60.0	76.0	6.0	41.0	122.0
Share redacted	2913	0.004	0.022	0.000	0.000	0.006
Number of disruptions	2913	0.413	0.672	0.000	0.250	1.000
Share of import disrupted	2496	0.018	0.052	0.000	0.005	0.042
Compustat						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	405	1.081	1.798	0.079	0.439	2.693
Volume (1000s TEUs)	405	2.644	8.007	0.085	0.694	5.896
Number of shippers	405	103.9	125.3	19.0	60.0	235.0
Share redacted	405	0.002	0.006	0.000	0.000	0.004
Sales(bn)	411	14.21	34.90	0.34	2.69	39.33
Total assets(bn)	410	33.47	173.86	0.25	2.59	44.52
Quarterly sales growth	395	0.011	0.097	-0.027	0.009	0.056
Number of disruptions	411	0.399	0.887	0.000	0.000	1.250
Share of import disrupted	411	0.005	0.014	0.000	0.000	0.014

Notes: Table D2 reports summary statistics for the underlying sample of U.S. firms for year 2010. Nominal variables have been converted to real ones using the Producer Price Index with 2015 being the base year.

Table D3: Summary Statistics, 2011

Full Sample						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	2881	0.490	1.413	0.013	0.204	1.002
Volume (1000s TEUs)	2881	1.152	6.001	0.010	0.257	2.113
Number of shippers	2881	55.5	68.8	5.0	40.0	115.0
Share redacted	2881	0.004	0.020	0.000	0.000	0.005
Number of disruptions	2881	0.453	0.696	0.000	0.250	1.250
Share of import disrupted	2458	0.021	0.053	0.000	0.006	0.050
Compustat						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	403	0.976	1.552	0.066	0.421	2.491
Volume (1000s TEUs)	403	2.359	7.182	0.063	0.660	5.525
Number of shippers	403	92.1	106.4	17.0	54.0	215.0
Share redacted	403	0.002	0.007	0.000	0.000	0.003
Sales(bn)	412	14.52	38.09	0.35	2.73	38.99
Total assets(bn)	412	32.41	164.63	0.25	2.56	42.17
Quarterly sales growth	398	-0.002	0.070	-0.042	-0.000	0.046
Number of disruptions	412	0.472	1.075	0.000	0.000	1.500
Share of import disrupted	412	0.005	0.012	0.000	0.000	0.016

Notes: Table D3 reports summary statistics for the underlying sample of U.S. firms for year 2011. Nominal variables have been converted to real ones using the Producer Price Index with 2015 being the base year.

Table D4: Summary Statistics, 2012

Full Sample						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	2982	0.530	1.509	0.031	0.225	1.096
Volume (1000s TEUs)	2982	1.206	5.940	0.024	0.291	2.315
Number of shippers	2982	62.9	76.7	12.0	44.0	124.0
Share redacted	2982	0.011	0.034	0.000	0.000	0.028
Number of disruptions	2982	0.460	0.833	0.000	0.250	1.250
Share of import disrupted	2390	0.021	0.051	0.000	0.007	0.050
Compustat						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	415	1.100	1.608	0.098	0.513	2.473
Volume (1000s TEUs)	415	2.621	8.459	0.102	0.955	6.172
Number of shippers	415	111.1	119.5	27.0	67.0	249.0
Share redacted	415	0.018	0.049	0.000	0.002	0.041
Sales(bn)	419	14.48	37.62	0.32	3.09	37.97
Total assets(bn)	415	35.50	171.05	0.26	2.84	50.28
Quarterly sales growth	401	0.007	0.071	-0.035	0.009	0.053
Number of disruptions	419	0.415	0.939	0.000	0.000	1.250
Share of import disrupted	419	0.005	0.015	0.000	0.000	0.016

Notes: Table D4 reports summary statistics for the underlying sample of U.S. firms for year 2012. Nominal variables have been converted to real ones using the Producer Price Index with 2015 being the base year.

Table D5: Summary Statistics, 2013

Full Sample						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	2972	0.696	2.016	0.023	0.279	1.379
Volume (1000s TEUs)	2972	1.541	6.530	0.021	0.355	2.875
Number of shippers	2972	67.1	87.1	8.0	48.0	129.0
Share redacted	2972	0.063	0.155	0.000	0.003	0.189
Number of disruptions	2972	0.517	0.795	0.000	0.250	1.250
Share of import disrupted	2620	0.016	0.041	0.000	0.005	0.039
Compustat						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	417	1.618	3.355	0.113	0.683	3.654
Volume (1000s TEUs)	417	3.807	11.113	0.116	1.122	8.506
Number of shippers	417	118.6	136.3	26.0	76.0	260.0
Share redacted	417	0.063	0.140	0.000	0.011	0.168
Sales(bn)	421	14.45	36.85	0.38	3.11	35.79
Total assets(bn)	420	36.10	173.61	0.29	2.91	51.10
Quarterly sales growth	406	0.003	0.083	-0.023	0.011	0.052
Number of disruptions	421	0.566	1.107	0.000	0.000	1.500
Share of import disrupted	421	0.005	0.012	0.000	0.000	0.013

Notes: Table D5 reports summary statistics for the underlying sample of U.S. firms for year 2013. Nominal variables have been converted to real ones using the Producer Price Index with 2015 being the base year.

Table D6: Summary Statistics, 2014

Full Sample						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	2997	0.766	2.445	0.024	0.290	1.523
Volume (1000s TEUs)	2997	1.691	7.116	0.021	0.382	3.269
Number of shippers	2997	69.8	96.2	9.0	48.0	136.0
Share redacted	2997	0.055	0.149	0.000	0.002	0.147
Number of disruptions	2997	0.608	0.961	0.000	0.250	1.500
Share of import disrupted	2629	0.018	0.038	0.000	0.007	0.046
Compustat						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	418	1.920	4.501	0.116	0.706	4.290
Volume (1000s TEUs)	418	4.523	13.126	0.139	1.140	9.735
Number of shippers	418	130.4	171.3	26.0	75.0	280.0
Share redacted	418	0.053	0.139	0.000	0.008	0.122
Sales(bn)	420	14.28	35.12	0.36	3.15	34.50
Total assets(bn)	417	36.33	177.05	0.30	3.10	50.37
Quarterly sales growth	408	0.004	0.084	-0.040	0.012	0.049
Number of disruptions	420	0.660	1.265	0.000	0.250	2.000
Share of import disrupted	420	0.005	0.010	0.000	0.000	0.014

Notes: Table D6 reports summary statistics for the underlying sample of U.S. firms for year 2014. Nominal variables have been converted to real ones using the Producer Price Index with 2015 being the base year.

Table D7: Summary Statistics, 2015

Full Sample						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	2992	0.773	2.425	0.028	0.299	1.547
Volume (1000s TEUs)	2992	1.782	7.401	0.023	0.411	3.364
Number of shippers	2992	70.3	98.8	9.0	50.0	131.0
Share redacted	2992	0.050	0.141	0.000	0.002	0.127
Number of disruptions	2992	0.627	1.030	0.000	0.250	1.500
Share of import disrupted	2623	0.019	0.046	0.000	0.007	0.045
Compustat						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	417	1.798	3.939	0.123	0.708	4.002
Volume (1000s TEUs)	417	4.211	9.534	0.162	1.189	10.161
Number of shippers	417	128.6	187.2	28.0	73.0	275.0
Share redacted	417	0.048	0.125	0.000	0.008	0.123
Sales(bn)	421	13.98	29.86	0.42	3.52	35.96
Total assets(bn)	420	39.57	188.02	0.36	3.47	57.06
Quarterly sales growth	411	0.012	0.074	-0.044	0.017	0.064
Number of disruptions	421	0.795	1.479	0.000	0.250	2.500
Share of import disrupted	421	0.006	0.014	0.000	0.000	0.018

Notes: Table D7 reports summary statistics for the underlying sample of U.S. firms for year 2015. Nominal variables have been converted to real ones using the Producer Price Index with 2015 being the base year.

Table D8: Summary Statistics, 2016

Full Sample						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	2993	0.723	2.244	0.020	0.282	1.459
Volume (1000s TEUs)	2993	1.655	7.152	0.019	0.381	3.243
Number of shippers	2993	68.2	100.2	8.0	48.0	126.0
Share redacted	2993	0.077	0.169	0.000	0.007	0.248
Number of disruptions	2993	0.604	1.046	0.000	0.250	1.500
Share of import disrupted	2614	0.017	0.041	0.000	0.007	0.040
Compustat						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	414	1.615	3.461	0.103	0.655	3.359
Volume (1000s TEUs)	414	3.646	7.621	0.115	1.167	8.119
Number of shippers	414	120.5	181.0	24.0	74.0	260.0
Share redacted	414	0.088	0.161	0.000	0.023	0.225
Sales(bn)	417	14.42	30.08	0.46	3.76	34.38
Total assets(bn)	416	42.63	199.80	0.43	3.69	65.12
Quarterly sales growth	407	-0.007	0.100	-0.058	0.002	0.043
Number of disruptions	417	0.777	1.660	0.000	0.250	2.250
Share of import disrupted	417	0.007	0.016	0.000	0.000	0.019

Notes: Table D8 reports summary statistics for the underlying sample of U.S. firms for year 2016. Nominal variables have been converted to real ones using the Producer Price Index with 2015 being the base year.

Table D9: Summary Statistics, 2017

Full Sample						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	2953	0.693	2.139	0.016	0.272	1.440
Volume (1000s TEUs)	2953	1.563	6.872	0.014	0.373	3.080
Number of shippers	2953	65.7	93.7	6.0	47.0	123.0
Share redacted	2953	0.096	0.193	0.000	0.011	0.314
Number of disruptions	2953	0.577	0.902	0.000	0.250	1.500
Share of import disrupted	2562	0.018	0.041	0.000	0.006	0.044
Compustat						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	416	1.435	2.934	0.083	0.629	3.184
Volume (1000s TEUs)	416	3.156	6.619	0.096	1.000	7.192
Number of shippers	416	109.9	165.7	19.0	66.0	241.0
Share redacted	416	0.099	0.162	0.000	0.035	0.272
Sales(bn)	420	15.10	32.93	0.48	3.87	36.00
Total assets(bn)	420	42.61	196.65	0.44	3.87	67.99
Quarterly sales growth	406	0.013	0.057	-0.020	0.008	0.060
Number of disruptions	420	0.605	1.150	0.000	0.000	2.000
Share of import disrupted	420	0.006	0.012	0.000	0.000	0.017

Notes: Table D9 reports summary statistics for the underlying sample of U.S. firms for year 2017. Nominal variables have been converted to real ones using the Producer Price Index with 2015 being the base year.

Table D10: Summary Statistics, 2018

Full Sample						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	2945	0.715	2.260	0.017	0.284	1.511
Volume (1000s TEUs)	2945	1.613	7.155	0.017	0.383	3.189
Number of shippers	2945	66.7	92.0	7.0	48.0	128.0
Share redacted	2945	0.094	0.191	0.000	0.010	0.323
Number of disruptions	2945	0.592	0.923	0.000	0.250	1.500
Share of import disrupted	2512	0.018	0.035	0.000	0.007	0.047
Compustat						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	421	1.435	2.583	0.070	0.620	3.431
Volume (1000s TEUs)	421	3.351	8.403	0.082	1.111	7.852
Number of shippers	421	108.9	148.9	17.0	70.0	239.0
Share redacted	421	0.110	0.184	0.000	0.024	0.335
Sales(bn)	424	15.80	36.63	0.48	4.16	36.95
Total assets(bn)	421	41.95	191.49	0.47	4.30	65.96
Quarterly sales growth	408	0.008	0.116	-0.035	0.003	0.048
Number of disruptions	424	0.596	1.094	0.000	0.000	2.000
Share of import disrupted	424	0.006	0.015	0.000	0.000	0.017

Notes: Table D10 reports summary statistics for the underlying sample of U.S. firms for year 2018. Nominal variables have been converted to real ones using the Producer Price Index with 2015 being the base year.

Table D11: Summary Statistics, 2020

Full Sample						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	2858	0.650	2.340	0.010	0.246	1.389
Volume (1000s TEUs)	2858	1.510	6.891	0.011	0.334	3.155
Number of shippers	2858	59.5	81.0	4.0	43.0	117.0
Share redacted	2858	0.079	0.178	0.000	0.009	0.224
Number of disruptions	2858	0.617	1.010	0.000	0.250	1.500
Share of import disrupted	2398	0.022	0.050	0.000	0.008	0.054
Compustat						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	412	1.140	1.758	0.059	0.540	2.736
Volume (1000s TEUs)	412	2.528	4.495	0.063	0.898	6.212
Number of shippers	412	97.1	125.2	15.0	65.0	204.0
Share redacted	412	0.082	0.164	0.000	0.019	0.212
Sales(bn)	418	15.73	36.18	0.47	4.29	36.49
Total assets(bn)	418	49.83	233.84	0.54	5.28	64.51
Quarterly sales growth	410	-0.000	0.097	-0.070	0.007	0.069
Number of disruptions	418	0.695	1.342	0.000	0.000	2.250
Share of import disrupted	418	0.006	0.013	0.000	0.000	0.019

Notes: Table D11 reports summary statistics for the underlying sample of U.S. firms for year 2020. Nominal variables have been converted to real ones using the Producer Price Index with 2015 being the base year.

Table D12: Summary Statistics, 2021

Full Sample						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	2827	0.729	2.809	0.013	0.272	1.522
Volume (1000s TEUs)	2827	1.663	7.764	0.014	0.394	3.416
Number of shippers	2827	62.6	83.1	5.0	45.0	123.0
Share redacted	2827	0.091	0.183	0.000	0.017	0.267
Number of disruptions	2827	0.598	1.007	0.000	0.250	1.500
Share of import disrupted	2376	0.021	0.044	0.000	0.008	0.053
Compustat						
Variable	Number of Firms	Mean	Std. Dev.	P10	P50	P90
Shipments (1000s)	403	1.291	2.038	0.054	0.576	3.089
Volume (1000s TEUs)	403	3.025	6.925	0.082	0.969	6.715
Number of shippers	403	101.9	133.1	15.0	66.0	208.0
Share redacted	403	0.094	0.164	0.000	0.026	0.286
Sales(bn)	408	14.31	34.77	0.46	3.55	32.44
Total assets(bn)	408	47.46	224.00	0.52	4.99	62.18
Quarterly sales growth	400	-0.032	0.147	-0.108	-0.026	0.067
Number of disruptions	408	0.583	1.068	0.000	0.000	2.000
Share of import disrupted	408	0.007	0.016	0.000	0.000	0.019

Notes: Table D12 reports summary statistics for the underlying sample of U.S. firms for year 2021. Nominal variables have been converted to real ones using the Producer Price Index with 2015 being the base year.

Table D13: Sales Growth and Supply Chain Disruptions, "6-0-1" Rule

	$\widetilde{\Delta}\text{Sales}^{t}_{i,t-1}$			$\widetilde{\Delta}\text{Sales}^{t-1}_{i,t-2}$	$\widetilde{\Delta}\text{Sales}^{t+1}_{i,t-1}$	$\widetilde{\Delta}\text{Sales}^{t+2}_{i,t-1}$	$\widetilde{\Delta}\text{Sales}^{t+3}_{i,t-1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbf{1}_{\text{Disruption}_{i,t}}$	-0.0127***	-0.0154***		0.0053	-0.0240***	-0.0141**	-0.0026
	(0.003)	(0.004)		(0.004)	(0.005)	(0.006)	(0.005)
Share disrupted$_{i,t}$			-0.4525***				
			(0.143)				
Year-Quarter FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	—	✓	✓	✓	✓	✓	✓
R^2	0.049	0.062	0.062	0.060	0.071	0.102	0.161
N	20595	20593	20593	20240	20181	19773	19356

Notes: See notes for Table 12.

Table D14: Sales Growth and Supply Chain Disruptions, "2-0-1" Rule

	$\widetilde{\Delta}\text{Sales}^{t}_{i,t-1}$			$\widetilde{\Delta}\text{Sales}^{t-1}_{i,t-2}$	$\widetilde{\Delta}\text{Sales}^{t+1}_{i,t-1}$	$\widetilde{\Delta}\text{Sales}^{t+2}_{i,t-1}$	$\widetilde{\Delta}\text{Sales}^{t+3}_{i,t-1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbf{1}_{\text{Disruption}_{i,t}}$	-0.0022	-0.0036		-0.0024	-0.0053	-0.0019	0.0001
	(0.002)	(0.003)		(0.003)	(0.004)	(0.004)	(0.004)
Share disrupted$_{i,t}$			-0.0989				
			(0.065)				
Year-Quarter FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	—	✓	✓	✓	✓	✓	✓
R^2	0.048	0.061	0.061	0.060	0.071	0.102	0.161
N	20595	20593	20593	20240	20181	19773	19356

Notes: See notes for Table 12.

Table D15: Sales Growth and Supply Chain Disruptions, "4-0-2" Rule

	$\widetilde{\Delta}\text{Sales}^{t}_{i,t-1}$			$\widetilde{\Delta}\text{Sales}^{t-1}_{i,t-2}$	$\widetilde{\Delta}\text{Sales}^{t+1}_{i,t-1}$	$\widetilde{\Delta}\text{Sales}^{t+2}_{i,t-1}$	$\widetilde{\Delta}\text{Sales}^{t+3}_{i,t-1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbf{1}_{\text{Disruption}_{i,t}}$	-0.0090***	-0.0115***		0.0026	-0.0204***	-0.0183***	-0.0088*
	(0.003)	(0.004)		(0.004)	(0.005)	(0.005)	(0.005)
Share disrupted$_{i,t}$			-0.5245***				
			(0.175)				
Year-Quarter FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	—	✓	✓	✓	✓	✓	✓
R^2	0.048	0.061	0.062	0.060	0.071	0.102	0.161
N	20595	20593	20593	20240	20181	19773	19356

Notes: See notes for Table 12.

Table D16: Sales Growth and Supply Chain Disruptions, "4-0-0" Rule

	$\widetilde{\Delta}\text{Sales}^{t}_{i,t-1}$			$\widetilde{\Delta}\text{Sales}^{t-1}_{i,t-2}$	$\widetilde{\Delta}\text{Sales}^{t+1}_{i,t-1}$	$\widetilde{\Delta}\text{Sales}^{t+2}_{i,t-1}$	$\widetilde{\Delta}\text{Sales}^{t+3}_{i,t-1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbf{1}_{\text{Disruption}_{i,t}}$	-0.0031	-0.0038		0.0012	-0.0040	-0.0077	-0.0066
	(0.002)	(0.003)		(0.003)	(0.004)	(0.005)	(0.005)
Share disrupted$_{i,t}$			-0.0351				
			(0.025)				
Year-Quarter FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	—	✓	✓	✓	✓	✓	✓
R^2	0.048	0.061	0.061	0.060	0.071	0.102	0.161
N	20595	20593	20593	20240	20181	19773	19356

Notes: See notes for Table 12.

Table D17: Sales Growth and Supply Chain Disruptions, "4-0-3/4" Rule

	$\widetilde{\Delta}\text{Sales}^{t}_{i,t-1}$			$\widetilde{\Delta}\text{Sales}^{t-1}_{i,t-2}$	$\widetilde{\Delta}\text{Sales}^{t+1}_{i,t-1}$	$\widetilde{\Delta}\text{Sales}^{t+2}_{i,t-1}$	$\widetilde{\Delta}\text{Sales}^{t+3}_{i,t-1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbf{1}_{\text{Disruption}_{i,t}}$	-0.0052	-0.0071*		0.0046	-0.0140***	-0.0101*	0.0048
	(0.003)	(0.004)		(0.004)	(0.005)	(0.005)	(0.005)
Share disrupted$_{i,t}$			-0.3248**				
			(0.151)				
Year-Quarter FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	—	✓	✓	✓	✓	✓	✓
R^2	0.048	0.061	0.061	0.060	0.071	0.102	0.161
N	20595	20593	20593	20240	20181	19773	19356

Notes: See notes for Table 12.

Table D18: Microeconomic Disasters and Cross-sectional Distributions

Investment Rates, $\frac{i}{k}$				
	$\mathbb{E}\left[\frac{i}{k}\right]$	$\sigma\left[\frac{i}{k}\right]$	$P\left[\left\|\frac{i}{k}\right\| > 0.2\right]$	$P\left[0 < \frac{i}{k} \leq 0.2\right]$
Data	0.10	0.16	0.14	0.86
Model $\lambda = 0$	0.10	0.11	0.17	0.79
Model $\lambda = 0.011$	0.10	0.12	0.17	0.78
Log Employment Changes, $\Delta \log n$				
	$P5010(\Delta \log n)$	$\sigma(\Delta \log n)$	$P[\Delta \log n \leq -3\sigma]$	$P[\Delta \log n \geq 3\sigma]$
Data	0.26	0.41	0.01	0.01
Model $\lambda = 0$	0.28	0.22	0.00	0.00
Model $\lambda = 0.011$	0.31	0.27	0.01	0.01

Notes: Table D18 characterizes the distribution of investment rates and employment changes in the steady-state of the model. Two versions of the model are considered: the one with jumps ($\lambda = 0.011$), and the one without ($\lambda = 0$). All figures are annual.

Table D19: Microeconomic Disasters and Business Cycle Statistics

	$\sigma(Y)$	$\sigma(C)/\sigma(Y)$	$\sigma(I)/\sigma(Y)$	$\sigma(\Delta C)$
Data	1.78	0.82	4.64	0.50
Model $\lambda = 0$	1.81	0.48	4.31	0.67
Model $\lambda = 0.011$	1.81	0.51	4.14	0.71
	$\sigma(\Delta Y)$	$\sigma(\Delta I)$	$AC_1(\Delta C)$	$AC_1(\Delta I)$
Data	1.00	2.63	0.34	0.41
Model $\lambda = 0$	1.40	5.99	0.04	0.01
Model $\lambda = 0.011$	1.40	5.72	0.04	0.02

Notes: Table D19 reports business cycle statistics for two versions of the model: the one with jumps ($\lambda = 0.011$), and the one without ($\lambda = 0$). The symbols have the following meaning: Y, output, C, consumption, I, investment, $\sigma(\cdot)$, standard deviation, $AC_1(\cdot)$, autocorrelation, $\rho(\cdot)$, correlation. Macro aggregates (C, Y, and I) were log-differenced and HP-filtered with the smoothing parameter of 1600. Business cycle statistics are quarterly. Model moments are the mean across 100 simulations of 500 quarters. We burn 200 first periods to reduce the impact of initial conditions.

References for Appendix

Chow, Melissa, Teresa C. Fort, Christopher Goetz, Nathan Goldschlag, James Lawrence, Elisabeth Ruth Perlman, Martha Stinson, and T. Kirk White, "Redesigning the Longitudinal Business Database," *CES Working Paper 21-08*, 2021.

Flaaen, Aaron, Flora Haberkorn, Logan Lewis, Anderson Monken, Justin Pierce, Rosemary Rhodes, and Madeleine Yi, "Bill of Lading Data in International Trade Research with an Application to the COVID-19 Pandemic," *Finance and Economics Discussion Series 2021-066. Washington: Board of Governors of the Federal Reserve System*, 2021.

Fort, Teresa and Shawn Klimek, "The Effects of Industry Classification Changes on U.S. Employment Composition," *manuscript*, 2016.

Haltiwanger, John, Ron Jarmin, and Javier Miranda, "Who Creates Jobs? Small vs. Large vs. Young," *Review of Economics and Statistics*, 2013, *95*, 347–361.

Jarmin, Ron and Javier Miranda, "The Longitudinal Business Database," *Center for Economic Studies, U.S. Census Bureau*, 2002.