Supply Chain Disruptions, Time to Build, and the Business Cycle*

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Abstract

We provide new evidence that (i) time to build is volatile and countercyclical, and that (ii) supply chain disruptions lengthen time to build. Motivated by these findings, we develop a general equilibrium model in which heterogeneous firms face non-convex adjustment costs and multi-period time to build. In the model, supply chain disruptions lengthen time to build. Calibrating the model to US micro data, we show that disruptions, which lengthen time to build by 1 month, depress GDP by 1% and aggregate TFP by 0.2%. Structural vector autoregressions corroborate the quantitative importance of supply chain disruptions.

Keywords: Time to build, supply chain disruptions, business cycles

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1 Introduction

Capital goods are complex and specific. An assembly line, for example, consists of many elements that all need to fit together: conveyor belts, robotic arms working along these belts, and the concrete foundation that supports the machines. In addition, capital goods are manufactured to the specific needs of an investing firm. Because of complexity and specificity, we observe a non-trivial time lag between the order and shipment of capital goods.[1] This delivery lag of capital goods, commonly labeled time to build, is assumed constant in modern business cycle theory.[2]

Capital goods are not only complex and specific, but also characterized by long supply chains. In fact, many intermediate goods, such as robotic arms, are themselves produced from intermediate goods.[3] Long supply chains are particularly vulnerable to disruptions, and disruptions may lengthen time to build. The sources of supply chain disruptions are manifold. Natural disasters can destroy establishments and block transportation routes. Changes in taxes or tariffs may lead to the re-organization of supply chains. Worker in production or transport go on strikes. Terror attacks and contagious diseases inhibit the flow of intermediate goods.

In the present paper, we document countercyclical variation in time to build and provide firm-level evidence that disruptions to the capital supply chain lengthen time to build. This novel empirical evidence motivates us to ask whether capital supply chain disruptions are quantitatively important for business cycles. We develop a heterogeneous firm general equilibrium model, that allows for multi-period time to build, and in which supply chain disruptions lengthen time to build. Calibrating the model to US micro data, we find that disruptions have sizable macroeconomic effects. A shock that lengthens time to build by one month lowers GDP by up to 1%.

To measure time to build, we use both aggregate and firm-level data on the order backlog of capital good producers from 1970 until 2016. We define time to build as the duration that new orders remain unfilled in the order books of capital good producers. Time to build exhibits substantial fluctuations over time, from three months to more than a year. In both aggregate and firm-level data, these fluctuations in time to build are countercyclical. Addressing various concerns in the measurement of time to build does not change this finding.

A possible driver of time to build fluctuations are disruptions in the supply chain of

[1] Relatedly, Belsley (1969) observes that most capital goods are produced to order, reflecting capital specificity, whereas consumption goods are typically produced to stock.

[2] Kydland and Prescott (1982) assumes four quarters time to build, but the standard assumption quickly shifted to one quarter, see, e.g., Prescott (1986) or Smets and Wouters (2007).

[3] Relatedly, data from Antras and Chor (2013) shows that capital good sectors are highly downstream, meaning they are relatively distant from primary factors of production.

capital producers which delay the supply of intermediate goods. However, whether or not such disruptions lengthen time to build is theoretically ambiguous. It depends on the buffer stock of inventories of intermediate goods, on the costs of modifying outstanding orders for capital goods, and on how easily the affected intermediate goods can be substituted. Using firm-level data, we show that supply chain disruptions, identified through natural disasters, do lengthen the time to build of the affected capital good producers.

Motivated by the empirical evidence, we develop a heterogeneous firm general equilibrium model. The model distinguishes between firms that supply capital and firms that demand capital. On the demand side, firms produce final goods by combining labor and specific capital. These final good producers invest in capital by signing order contracts with engineering firms. The engineering firms devise blueprints and search for suppliers of the required intermediate goods on a frictional market.[4] After the engineering firm matches with a supplier, the ordered capital goods are produced and delivered. Time to build arises from matching frictions between engineering firms and suppliers. In this setup, supply chain disruptions can be modeled as negative matching efficiency shocks or as positive shocks to the costs of suppliers. Both types of shocks lengthen lengthen time to build in equilibrium. Ultimately, their effects on the rest of the model economy are indistinguishable from each other, and our quantitative analysis focuses on matching efficiency shocks. In addition to the endogenous time to build friction, investment is partially irreversible, which gives rise to lumpy investment and wait-and-see behavior.

In the model, supply chain disruptions are contractionary through two channels. First, a delay in the delivery of outstanding orders reduces contemporaneous investment and thus production. Second, longer time to build worsens the alignment between firm-specific productivity and capital. A longer waiting time raises the ex-ante uncertainty about productivity in the usage period of the ordered capital goods. As a result, firms invest less frequently. Even if they do invest, a longer waiting time implies that ex-ante ordered investments tend to be further away from their ex-post optimal levels. Hence, longer time to build exacerbates capital misallocation across firms and aggregate total factor productivity (TFP) falls.

The model is calibrated to US data and jointly targets moments of the investment rate distribution and aggregate fluctuations in time to build. To solve the model, we adapt the Reiter (2009) method. In the calibrated model, supply chain disruptions that raise time to build by one month cause a sharp 8% drop in investment. The direct effect of delayed delivery is important for the short-term effects. Aggregate output also features a sharp initial drop of 1%, but reverts back to steady state slowly after the first quarter. The persistence is

[4] Previous work that incorporates frictional capital markets into business cycle models includes Kurmann and Petrosky-Nadeau (2007) and Ottonello (2015).

partly due to a gradual response in aggregate TFP, which falls but attains its peak response of 0.22% only 6 quarters after the shock. This reflects the indirect effect of the disruption shock, which operates through increased capital misallocation, and explains about half of the medium-term response in aggregate output. We further use the model to study the extent of post-war business cycle fluctuations that can be attributed to supply chain disruptions. Supply chain disruptions explain up to half of the decline in output and investment during the early 1990s recession and the Great Recession.

Finally, we use a structural vector autoregressive (VAR) model to corroborate the quantitative importance of supply chain disruptions, which we identify through timing restrictions. In medium-scale VAR models fitted to US data, we find that disruptions have large macroeconomic impact. A one standard deviation shock lowers GDP by 0.5% and aggregate TFP by 1.0%.

The remainder of this paper is organized as follows. After a brief review of the related literature, Section 2 presents the empirical evidence. Section 3 proposes an analytical framework to study the misallocation effects of time to build. Section 4 develops the full business cycle model. Section 5 presents the calibration and quantitative results of the model. Section 6 provides VAR evidence. Section 7 concludes and an appendix follows.

Related Literature

The notion of time as a factor in the production of capital goods has deep roots in the history of economic research going back to Ricardo (1817) and von Böhm-Bawerk (1891). Nonetheless, whether or not time to build fluctuates with the business cycle has not been firmly established. Using aggregate data, Zarnowitz (1962) documents procyclical time to build between 1946 and 1959, while more recently Nalewaik and Pinto (2015) documents countercylical time to build post-1968.[5] We reconfirm the latter finding in both aggregate and firm-level data. Firm-level data helps us to reject the concern that measured time to build fluctuations are primarily driven by sales fluctuations. We focus on equipment capital goods, which constitutes the bulk of non-residential investment. For nonresidential construction, Brooks (2000) documents acyclical time to build. For residential construction, Oh and Yoon (2020) documents countercyclical time to build.

Another strand of related literature studies the role of production networks for the propagation of shocks. Barrot and Sauvagnat (2016), Carvalho et al. (2016), and Boehm et al. (2018) study the propagation of natural disasters. While these papers focus on sales responses, another important consequence of natural disasters are time delays, see Hicks

[5] According to Popkin (1965), procyclical measured time to build in the early post-WWII period may be due to large demand for military equipment around the Korean War.

(1970). We contribute to this literature by showing that upstream disruptions lengthen time to build. In our model, the indirect effects of longer time to build through capital misallocation are as important as the direct quantity effects. Relatedly, Greenwood et al. (1988), Fisher (2006), and Justiniano et al. (2010) study investment-specific technology shocks. Supply chain disruptions in our model can be considered a novel type of such technology shocks. Disruptions operate primarily through delivery delays, while the technology shocks in the preceding literature operate through the investment price. Also related is a management literature on supply chain disruptions. E.g., Hendricks and Singhal (2005) and Westerburg and Bode (2018) study returns after disruptions and the role of mitigation strategies.

Finally, this paper relates to a literature that studies capital misallocation over the business cycle. Eisfeldt and Rampini (2006) provides empirical evidence that capital becomes more misallocated during recessions. Capital misallocation is a potent transmission mechanism for a variety of shocks: e.g., aggregate productivity shocks, see Khan and Thomas (2008) and Bachmann et al. (2013), financial shocks, see Khan and Thomas (2013), and uncertainty shocks, see Bloom (2009). Similar to the transmission of uncertainty shocks in Bloom (2009), supply chain disruptions increase the real option value of waiting.

2 Empirical evidence

We establish that time to build – the time gap between order and delivery of capital goods – is countercylical, and that capital supply chain disruptions lengthen time to build.

2.1 Countercyclical fluctuations in time to build

Data. We measure time to build using data on the order books of capital good producers. To ensure a broad empirical basis, we use both aggregate and firm-level data.

We use aggregate data based on the *Manufacturers' Shipments, Inventories, and Orders (M3) Survey*, which is maintained by the US Census. The survey covers two third of manufacturers with annual sales above 500 million USD and some smaller manufacturers to improve sectoral coverage. The M3 survey is most prominently used to compute quarterly investment by the Bureau of Economic Analysis.[6] We focus on the non-defense equipment good sector, for which the Census provides a publicly available monthly series of the order backlog and shipment going back to 1968. Shipments (sales) is the value of goods delivered during the month. A new order is a legally binding intention to buy for immediate or future delivery. The survey records the value new orders net of order modifications, where modifications

[6] See *Concepts and Methods of the U.S. National Income and Product Accounts* (2014, ch. 3).

include cancellations, adjustments, and price changes. The order backlog is the value of orders (net of modifications) that have not yet fully passed through the sales account.

In addition, we use firm-level data from *Compustat*, which covers publicly listed US corporations. Since 1970, SEC regulation requires these corporations to disclose the value of their order backlog in their annual 10-K filings.[7] Compustat data on order backlogs has been used to predict firm performance, both by financial analysts and in academic research, e.g., Lev and Thiagarajan (1993). We define capital good producers as firms with SIC codes between 35–38. This closely matches the definition of equipment goods in the M3 survey.

Time to build measurement. We measure time to build, the time gap between the order and delivery of capital goods, as the duration that new orders remain unfilled in the order books of capital good producers. Let S_t denote the aggregate flow value of capital good producers' sales, and B_t the aggregate stock value of backlogged orders of capital good producers at the beginning of the period. Our baseline measure of time to build is the backlog ratio

$$TTB_t \equiv \frac{B_t}{S_t}. \tag{2.1}$$

Using the backlog ratio as measure of time to build dates back to Holt et al. (1960) and Zarnowitz (1962). Absent sales fluctuations, the backlog ratio exactly captures the (sales-weighted) average time between order and delivery if outstanding orders are shipped according to a first-in-first-out protocol. Fluctuations in aggregate and firm-level sales can drive a wedge between average time to build and the backlog ratio. We revisit the role of fluctuations in firm-level sales toward the end of this subsection. To study the role of fluctuations in aggregate sales, we propose an alternative time to build measure. Instead of computing the duration of a new order in the backlog from current sales, we use future sales realizations. We compute time to build as the number of periods it takes until the current order backlog is exhausted by future realized sales, and linear interpolate sales in between periods to obtain fractions of periods. Formally,

$$\widetilde{TTB}_t \equiv \left\{ \text{interpolated months of realized future sales until } B_t \text{ is depleted} \right\}. \tag{2.2}$$

Using the monthly *aggregate data* released by the Census, we construct both the backlog ratio and the alternative time to build measure in (2.2). Using the annual *firm-level data*, we construct the backlog ratio at the aggregate and firm level. We clean the firm-level data as

[7] See SEC regulation §229 item 101(c) (VIII). 10-K filings on order backlogs are subject to audits, see Statement of Auditing Standards AU §550.

follows. We keep firms in SIC sectors 35–38 and drop firm-year observations if sales or the order backlog are missing, zero, or negative. It is an accounting identity that the aggregate backlog ratio equals the weighted mean of firm-level backlog ratios

$$TTB_t = \sum_j w_{jt} \cdot TTB_{jt}, \tag{2.3}$$

where firm j's weight is its sales shares, $w_{jt} = S_{jt}/S_t$, and $TTB_{jt} = B_{jt}/S_{jt}$. We discard firm-quarter observations with TTB_{jt} below 0.1 months or above 10 years.

Time to build in aggregate data. Figure 1 shows the evolution of time to build during the last five decades. The upper panel is based on Census M3 data. Time to build, measured by the backlog ratio, fluctuates between three and ten months. These fluctuations are countercyclical. The correlation of quarterly real GDP growth with log time to build is -0.28 and the correlation with time to build growth is -0.20. In addition, time to build is longest during recessions periods. The alternative time to build series in (2.2) closely matches the backlog ratio in Figure 1, and it has almost the same correlation with the business cycle. This is primarily because the monthly sales series has an auto-correlation close to unity, 0.995 to be precise. Hence, current sales and future sales differ by relatively little at time horizons between three to ten months. The fact the two time to build series are almost identical invalidates the concern that the countercyclicality of the backlog ratio is a statistical artefact of not capturing fluctuations in aggregate sales.

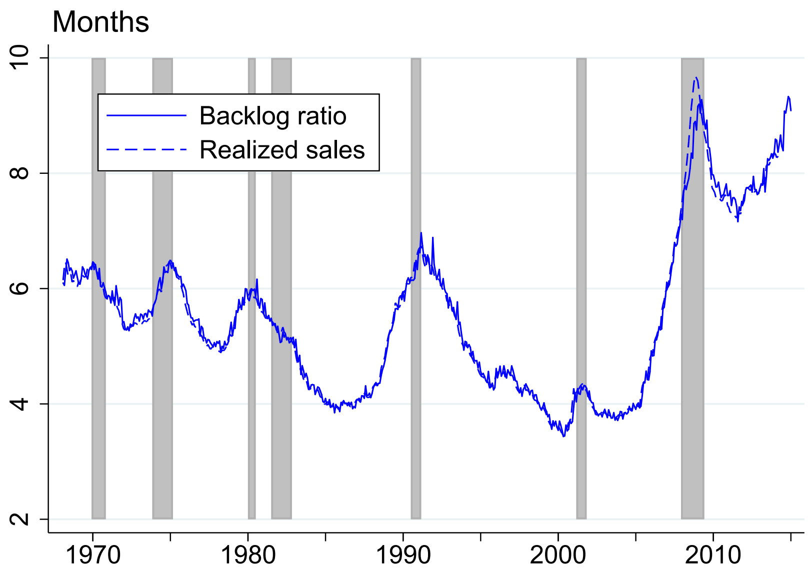
From a statistical viewpoint, the fluctuations in the backlog ratio are driven by fluctuations in sales and backlog of equipment goods. Figure 7 in the Appendix plots the time series of aggregate order backlog, sales, and new orders based on Census M3 data. These series are connected through the law of motion, $B_{t+1} = B_t - S_t + N_t$, where N_t denotes new orders. By far the most volatile are new orders, while sales is somewhat less volatile than the order backlog.[8] While new orders are procyclical, sales and order backlog are lagged procyclical.[9] The fact that sales of capital goods is lagged procyclical is little surprising in the presence of time to build. What is more surprising is that the order backlog is not countercyclical. Why do capital good producers not deplete their order backlog during recessions in order to smooth sales? A possible explanation is that firms cannot reduce their backlog during recessions because of supply shocks.

[8]The standard deviation of quarterly growth rates are 3.2% for sales, 3.7% for backlog, and 10.0% for new orders.

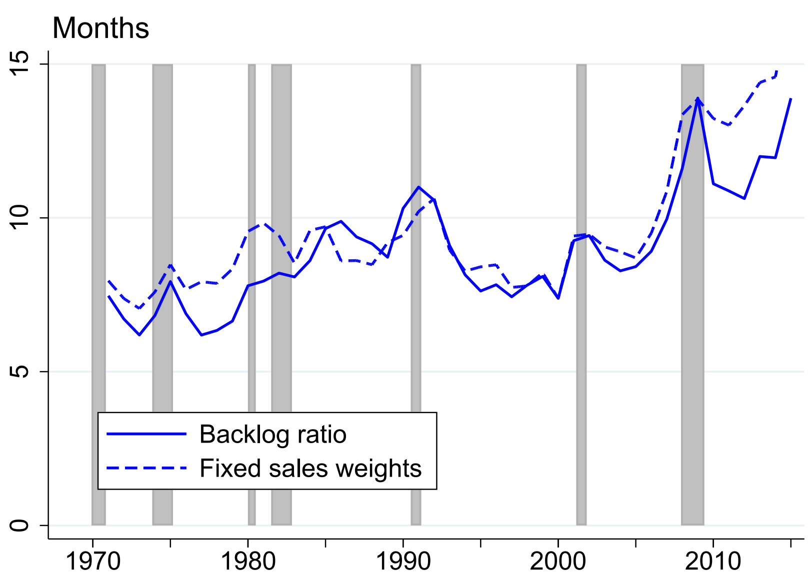
[9]The correlation of new orders growth is largest with contemporaneous real GDP growth (in contrast to real GDP growth of the preceding and succeeding 8 quarters). For sales and backlog growth the correlation is largest with real GDP growth lagged by 1 and 4 quarters, respectively.

Figure 1: Time to build

(a) Monthly aggregate data



(b) Annual firm-level data



Notes: The solid line in panel (a) is the order backlog ratio to monthly shipments for non-defense equipment goods. The dashed line is the number of months of future sales realizations that are required to deplete the current order backlog, linearly interpolating between months. In panel (b), the solid line shows the sales-weighted mean across firms. The dashed line is the sales-weighted mean backlog ratio when fixing firm-specific sales weights based on sales in the year 2000. Shaded, gray areas indicate NBER recession dates.

Time to build in firm-level data. The lower panel of Figure 1 shows the evolution of time to build based on firm-level data. The backlog ratio fluctuates substantially and tends to peak during recessions, consistent with the aggregate data. Time to build in the firm-level data is also negatively correlated with GDP growth. The correlation of annual real GDP growth with log time to build is -0.45 and the correlation with time to build growth is -0.52.

The aggregate backlog ratio is equivalent to the sales-weighted mean firm-level backlog ratio, see (2.3). Fluctuations in the aggregate backlog ratio are potentially driven by cyclical changes in the sales composition. To be more precise, suppose the sales of capital goods with higher average time to build were less volatile over the business cycle than the sales of capital goods with lower average time to build. Then the aggregate backlog ratio would be countercyclical even if the firm-specific backlog ratios are constant over the cycle. We address this concern in two ways.

First, we study the evolution of the aggregate backlog ratio when keeping the firm-specific sales weights in (2.3) fixed over time. We assign fixed sales weights according to firm-level sales in the year 2000. This means we effectively drop firms without a sales observation in 2000.[10] The dashed line in the lower panel of Figure 1 shows the time series evolution of the 'fixed sales weights' backlog ratio. The series is remarkably similar to the baseline backlog ratio. In addition, the business cycle correlation is fairly unchanged under fixed sales weights.[11] These findings suggest that shifts in the sales composition toward firms with higher average time to build are unlikely the reason for countercyclical time to build.

Second, we decompose changes in aggregate time to build into three contributing factors. Based on (2.3), we propose the following decomposition

$$\Delta TTB_t = \sum_j w_{jt-1} \cdot \Delta TTB_{jt} + \sum_j \Delta w_{jt} \cdot TTB_{jt-1} + \sum_j \Delta w_{jt} \cdot \Delta TTB_{jt}. \tag{2.4}$$

The first term captures changes in firm-level time to build, the second term changes in the sales shares, and the third term directed change. The business cycle correlation of ΔTTB_t is mostly captured by the first term, whereas the other two terms are less correlated with the cycle.[12] This reconfirms the finding under fixed sales weights in Figure 1. Changes in the firm-specific backlog ratio rather than changes in sales are central for understanding countercyclical movements in aggregate time to build. We further apply a variance decomposition to (2.4). The variance of the first term accounts for 38% of the variance in ΔTTB_t. If we

[10] The results are robust to fixing sales weights at year 1995 or 2005 sales.

[11] The correlation of annual real GDP growth with the log fixed-weights backlog ratio -0.43 and the correlation with time to build growth under fixed weights is -0.39.

[12] The correlation with annual real GDP growth is -0.41 for ΔTTB_t, -0.42 for the first term, -0.22 for the second term, and -0.02 for the third term.

add the covariance between the first and the second/third term, the first terms accounts for 55% of the variance in ΔTTB_t. The variance of the second term accounts for most of the remaining variance in ΔTTB_t.

2.2 Supply chain disruptions and time to build

We provide firm-level evidence that time to build lengthens after a supplier is hit by a natural disaster, and after periods in which annual reports describe increased adverse supply risks.

Supply chains and natural disasters. We think of supply chain disruptions as shocks that delay the supply of intermediate goods. However, whether or not such disruptions lengthen time to build is theoretically ambiguous. If capital good producers hold sufficient inventory of intermediate goods time to build may not respond to disruptions. Similarly, time to build may not respond if producers can easily and quickly find substitutes for the affected intermediate goods. However, Barrot and Sauvagnat (2016) and Boehm et al. (2018) show that intermediate goods are barely substituted in the short term. They also document an adverse sales response to disruptions, which suggests insufficient inventory holdings.

To identify the impact of supply chain disruptions on time to build, we use an estimation strategy similar to Barrot and Sauvagnat (2016), who study the effect supply chain disruptions mainly on sales. We use county-level data on natural disasters obtained from the SHELDUS database. We focus on major disasters defined by an economic damage above one billion USD (in 2013 prices). 41 such major disasters occurred between 1980 and 2013. We link disasters to firms through the county location of firms' headquarters.[13] We further use the Compustat Segment files to identify firms' principal customers in any given year.[14]

We regress log time to build of an individual capital good producing firm, measured by the backlog ratio, on two types of dummy variables. The first one assumes the value one if the capital good producer itself is located in a county that is hit by a major natural disaster. The second type of dummy is one if at least one supplier to the capital good producer is located in a disaster-hit county *and* if the county of the affected supplier is at least 300 miles away from the linked capital good producer. We condition on sufficient distance to mitigate the problem that supplier and capital good producer may be affected by the same change in local demand conditions after the disaster. We further include firm and year fixed effects, and, in some specifications, a dummy for tertiles of the number of suppliers.

[13] Of course, many firms in our sample have establishments in different locations. We expect that only using the headquarter county will bias our results toward zero.

[14] More details on the disaster data and on the supplier-customer links can be found in Barrot and Sauvagnat (2016). Our effective sample size is substantially smaller than theirs because we focus on capital good producers and use annual instead of quarterly data.

Table 1 summarizes the empirical findings. The second and third columns show that a capital good producer's time to build significantly increases by about 10% in years during which a natural disaster hits either the capital good producer directly or at least one of its suppliers. The effects are robust to controlling for the number of suppliers. The fourth and fifth column present the results when adding one-year lags of both types of disaster dummies. The point estimates that capture the time to build response to contemporaneous natural disasters are about 9%, quite similar to the specification without lagged disasters. In addition, the response of time to build to supply chain disruptions, i.e. natural disasters hitting a supplier, remain statistically significant. Interestingly, the effects of disruptions

Table 1: Firm-level evidence on supply disruptions and time to build

	Time to build (t) (in logs)				
Disaster hits at least one supplier (t)	0.100 (0.043)	0.087 (0.038)	0.093 (0.041)	0.081 (0.037)	
Disaster hits at least one supplier (t–1)			0.097 (0.044)	0.089 (0.041)	
Disaster hits capital good producer (t)	0.108 (0.051)	0.107 (0.055)	0.094 (0.059)	0.094 (0.061)	
Disaster hits capital good producer (t–1)			0.048 (0.0453)	0.047 (0.054)	
Supply risk exposure (t–1)					0.029 (0.018)
Demand risk exposure (t–1)					-0.033 (0.023)
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Number of suppliers	No	Yes	No	Yes	No
R^2	0.0806	0.0824	0.0856	0.0876	0.140
Observations	23,446		20,789		3,136
Years	1980–2013				2006–2013

Notes: Columns 2-5 present the estimates from panel regressions of log time to build on dummies indicating whether the firm itself or at least one of their suppliers is located in a county (at least 300 miles away from the firm's location) that is hit by a major natural disaster in the same year or the preceding year. The last column presents the estimates of time to build on the number of distinct adverse supply and demand risk topics described in the firm's annual report of the preceding year. Standard errors are clustered at the firm level and presented in parentheses.

persist into the subsequent year. The effect of lagged supply chain disruptions are of similar magnitude and statistical significance as the effect of contemporaneous disruptions.

Exposure to supply risk. To complement the empirical analysis, we study the effect of broad categories of supply risks on time to build. Since 2005, SEC regulation requires corporations to disclose their (self-assessed) exposures to important *downside* risks in the risk section of their annual reports. Westerburg and Bode (2018) apply text learning to extract supply and demand risk topics from these risk sections. Examples of adverse supply risk exposures include:

> *"As we rely on a limited number of third parties to [..] supply required parts and materials, we are exposed to significant supplier risks."*
>
> *"We are dependent on technology systems and third-party content that are beyond our control."*
>
> *"The impact of natural disasters could negatively impact our supply chain."*

Demand risks include market competition, product approvals, and market acceptance. Using their data, the last column of Table 1 show the effects of supply and demand risk exposures on time to build of capital good producers. After periods of heightened supply risk exposure, time to build lengthens. The response is significant at the 10% level. This finding further supports the notion that supply shocks affect time to build. Instead, heightened demand risks shorten the capital producer's time to build, albeit the effect is insignificant.

3 Analytical framework

We analytically characterize the effects of longer time to build on aggregate TFP through capital misallocation in a stripped-down tractable model. This helps to build intuition and to gauge the quantitative bite of the mechanism. The main model of this paper, introduced in the subsequent section, is analytically intractable but richer in various dimensions.

The model is populated by a fixed mass of perfectly competitive firms. Firms are ex-ante identical and use specific capital k_{jt} and labor ℓ_{jt} to produce a homogeneous final good

$$y_{jt} = x_{jt} k_{jt}^{\alpha} \ell_{jt}^{\nu}, \quad 0 < \alpha + \nu < 1. \tag{3.1}$$

Idiosyncratic productivity, x_{jt}, follows an AR(1) process in logs

$$\log(x_{jt+1}) = \rho_x \log(x_{jt}) + \sigma_x \epsilon_{jt+1}, \quad 0 < \rho_x < 1, \quad \epsilon_{jt+1} \overset{iid}{\sim} \mathcal{N}(0,1). \tag{3.2}$$

Firms are price-takers, w_t is the wage rate and r_t the user cost of capital. Period profits are

$$\pi_{jt} = x_{jt}k_{jt}^{\alpha}\ell_{jt}^{\nu} - w_t\ell_{jt} - r_tk_{jt}. \tag{3.3}$$

Labor is adjusted every period and without frictions. Capital adjustment is subject to τ periods time to build but no other adjustment friction. In period t, the firm needs to choose how much capital to employ in period $t+\tau$ in order to maximize expected period $t+\tau$ profits. This yields

$$k_{j,t,t+\tau} = \left(\frac{\alpha}{\mathbb{E}_t[r_{t+\tau}]}\right)^{\frac{1-\nu}{1-\alpha-\nu}} \left(\frac{\nu}{\mathbb{E}_t[w_{t+\tau}]}\right)^{\frac{\nu}{1-\alpha-\nu}} \mathbb{E}_t[x_{jt+\tau}^{\frac{1}{1-\nu}}]^{\frac{1-\nu}{1-\alpha-\nu}}. \tag{3.4}$$

We study the aggregate implications of changes in time to build using comparative statics. In steady state with τ periods time to build, the aggregate capital stock is $K_\tau = \int k_{j,t,t+\tau}dj$, and aggregates L_τ, Y_τ are constructed analogously. We define aggregate TFP as model-consistent Solow residual, $\text{TFP}_\tau \equiv \log Y_\tau - \alpha \log K_\tau - \nu \log L_\tau$, which can be simplified to

$$\text{TFP}_\tau = \frac{1}{2}\frac{1}{1-\alpha-\nu}\frac{1}{1-\rho_x^2}\sigma_x^2 - \frac{1}{2}\frac{\alpha}{(1-\nu)(1-\nu-\alpha)}\frac{1-\rho_x^{2\tau}}{1-\rho_x^2}\sigma_x^2. \tag{3.5}$$

Qualitatively, longer time to build (τ) unambiguously lowers aggregate TFP. Quantitatively, the TFP loss of time to build depends on three factors.[15]

a) The TFP loss grows in α as capital misallocation becomes more important for TFP.

b) The TFP loss grows in $(\alpha + \nu)$ because optimal firm size increases more steeply in productivity. As time to build prevents quick size adjustment, deviations from optimal size and hence misallocation increases.

c) The TFP loss grows in ρ_x and σ_x because the productivity variance while waiting for delivery, $\mathbb{V}_t[\log x_{jt+\tau}] = \frac{1-\rho_x^{2\tau}}{1-\rho_x^2}\sigma_x^2$, increases, which raises capital misallocation.

To study the quantitative bite of capital misallocation, we set α, ν, ρ_x, and σ_x to match the estimates in Cooper and Haltiwanger (2006). More details on the parameter estimates and a brief survey of alternative estimates are provided in Appendix B. We then consider an increase in time to build from five to six months, which is roughly a one standard deviation increase beyond the mean of the series in Figure 1. One month longer time to build reduces

[15] Another factor is the capital-labor substitution elasticity. An elasticity of 0.5, consistent with the evidence surveyed in Chirinko (2008), would further strengthen the quantitative impact of time to build on aggregate TFP.

aggregate TFP by 0.21%. To computed the GDP effects in general equilibrium, we need to specify preferences. With additively separable preferences, $U = \frac{C^{1-\sigma}-1}{1-\sigma} - \psi \frac{L^{1+\phi}}{1+\phi}$, the log-change in aggregate GDP is $\Delta_\tau \log Y_\tau = \frac{1}{1-\nu} \Delta_\tau TFP_\tau$. The aggregate TFP loss then translates into a GDP loss of 0.53%.

The TFP and GDP effects underline the quantitative bite of the mechanism. In the full model we present next the effects may be smaller or larger. First, we have sofar focused on the long-run effects, whereas the short-run effects are possibly smaller because capital misallocation builds up gradually when idiosyncratic productivity is persistent. Second, this analytical framework abstracts from capital adjustment frictions other than time to build. Longer time to build raises the effective uncertainty of an investment project, and in response firms may postpone capital adjustment which further raises capital misallocation.

4 Model

We develop a real business cycle model to study capital supply chain disruptions. In the model, final good producers vary in their productivity and use specific capital. Investment is partially irreversible and subject to time to build. Time to build arises from frictions on the market for intermediate goods, which are used for capital good production. Supply chain disruptions, which lengthen time to build, are modeled as capital-specific cost shocks or shocks to the matching friction.

4.1 Households

The economy is populated by a unit measure of identical households that take prices as given. The households value consumption C_t and leisure $1 - L_t$, and the per-period time endowment is 1. The households are mobile to supply labor across sectors of the economy. They receive labor income $w_t L_t$ and hold shares A_t in a mutual fund of all firms in the economy. Shares are traded at price P_t and pay dividend Π_t. The household problem is

$$\max_{\{C_t, L_t, A_{t+1}\}_{t=0}^{\infty}} \mathbb{E} \sum_{t=0}^{\infty} \beta^t U(C_t, L_t) \quad \text{s.t.} \quad C_t + P_t A_{t+1} = w_t L_t + (P_t + \Pi_t) A_t. \tag{4.1}$$

The first-order condition for shares yields the stochastic discount factor

$$Q_{t,t+1} = \beta \frac{U_C(C_{t+1}, L_{t+1})}{U_C(C_t, L_t)}. \tag{4.2}$$

by which firms discount future profits.

4.2 Engineering firms and intermediate good suppliers

The capital supply side of the model is motivated by the empirical evidence in Section 2, which shows that shocks to intermediate good suppliers propagate downstream to capital good producers and lengthen time to build.

In the model, engineering firms (short: engineers) produce and receive order for specific capital goods from final good producers. To produce capital, engineers devise blueprints that specify the required intermediate goods. Intermediate good suppliers (short: suppliers) produce these inputs and supply them to engineers on a frictional market. Think of a single supplier as a shortcut for a network of suppliers that produce all the inputs required to produce the ordered capital good. An engineer that is matched with a supplier receives the required inputs, produces the ordered capital good and delivers it at the end of the period.

We assume a large mass of engineers and suppliers. Unmatched engineers and suppliers are active, meaning they can match with the other side of the frictional market, only in periods in which they incur fixed costs of operations. These costs are ξ overhead workers for engineers and ξa_t for suppliers, where a_t is an exogenous cost parameter. The mass of unmatched active engineers be E_t and the mass of unmatched active suppliers be S_t. The matching technology between engineers and suppliers is

$$M_t = m_t E_t^{\eta} S_t^{1-\eta}, \quad 0 < \eta < 1, \tag{4.3}$$

where m_t denotes exogenous matching efficiency. We define market tightness as $\theta_t = E_t/S_t$. For an engineer, the probability of filling an order is $q_t = m_t \theta_t^{\eta-1}$, and for a supplier the matching probability is $\theta_t q_t$.

Let us next consider an engineer with an outstanding order of i_t units of capital goods. When the engineer is matched with a supplier, the engineer purchases a quantity i_t of intermediate goods at per-unit price p_t^S. The supplier produces the intermediate goods from final goods at unit marginal costs. The value of an unmatched and matched active supplier are, respectively,

$$V_t^S = -\xi a_t w_t + \theta_t q_t J_t^S + (1-\theta_t q_t)\mathbb{E}_t[Q_{t,t+1} V_{t+1}^S], \quad \text{and} \quad J_t^S = p_t^S i_t - i_t. \tag{4.4}$$

After receiving i_t intermediate goods, the engineer transforms them into i_t capital goods and sells them at per-unit price p_t^E to the final good producer from which it has received the offer. The market for capital good orders is a competitive spot market, and engineers commit to order contracts. Ordering final good producers can only hire one engineering firm in any period of time. Thus, the number of engineers equals the number of orders. The value of an unmatched and matched active engineer are, respectively,

$$V_t^E = -\xi w_t + q_t J_t^E + (1-q_t)\mathbb{E}_t[Q_{t,t+1}V_{t+1}^E], \quad \text{and} \quad J_t^E = p_t^E i_t - p_t^S i_t. \tag{4.5}$$

There is free entry of suppliers and engineers are competitive. Hence,

$$V_t^S = V_t^E = 0. \tag{4.6}$$

When matched, engineer and supplier split the match surplus by Nash bargaining over the unit price p_t^S, where ϕ is the engineer's bargaining weight,

$$\max_{p_t^S}(J_t^E - V_t^E)^{\phi}(J_t^S - V_t^S)^{1-\phi}, \quad 0 < \phi < 1. \tag{4.7}$$

We have implicitly assumed that matches between engineers and suppliers are short-lived. This assumption conforms with the notion that capital goods are specific and suppliers represent a collection of suppliers. The assumption also avoids technical complications.[16]

The capital supply side of the model captures two types of supply chain shocks. Shocks to supplier costs, a_t, and shocks to matching efficiency, m_t. Both follow log AR(1) processes

$$\log(a_t) = (1-\rho^a)\log(\mu^a) + \rho^a \log(a_{t-1}) + \sigma^a \epsilon_t^a, \quad \epsilon_t^a \overset{iid}{\sim} \mathcal{N}(0,1), \tag{4.8}$$

$$\log(m_t) = (1-\rho^m)\log(\mu^m) + \rho^m \log(m_{t-1}) + \sigma^m \epsilon_t^m, \quad \epsilon_t^m \overset{iid}{\sim} \mathcal{N}(0,1). \tag{4.9}$$

Both a_t and m_t affect the order filling probability q_t and thereby time to build in equilibrium. We discuss the equilibrium effects of a_t and m_t in more detail at the end of this section.

Finally, we make a technical assumption that facilitates the numerical model solution. Instead of one capital market, we assume there is a continuum of capital submarkets, all of which are described by the above setup, and which only differ in their overhead cost parameter ξ. The cross-sectional distribution of ξ-submarkets is described by the *cdf* G of ξ, defined over support $\mathbb{R}^+$. When ordering specific capital goods, final good producers randomly access one of these ξ-submarkets. It will later become clear that this setup implies *stochastic* fixed capital adjustment costs for final good producers.

[16] If some engineers remain matched with suppliers for multiple periods, they could deliver capital goods with one-period time to build. That would require us to specify how final good producers are allocated to matched and unmatched engineers.

4.3 Final good producers

The economy is populated by a unit mass of final good producers, indexed by j. Producers are perfectly competitive and operate a decreasing-returns-to-scale technology that combines labor and specific capital to produce a homogeneous final good

$$y_{jt} = z_t x_{jt} k_{jt}^{\alpha} \ell_{jt}^{\nu}, \quad 0 < \alpha + \nu < 1, \tag{4.10}$$

where z_t denotes aggregate productivity, and x_{jt} idiosyncratic productivity. Both idiosyncratic and aggregate productivity follow independent log AR(1) processes described by parameters (ρ_x,σ_x) and (ρ_z,σ_z), cf. Section 3. Labor adjustment is frictionless and we define the gross cash flow as

$$cf_{jt} = \max_{\ell_{jt} \in \mathbb{R}^+} \left\{ z_t x_{jt} k_{jt}^{\alpha} \ell_{jt}^{\nu} - w_t \ell_{jt} \right\}. \tag{4.11}$$

Firm-specific capital evolves over time according to $k_{jt+1} = (1-\delta)k_{jt} + i_{jt}$, where δ denotes the depreciation rate and i_{jt} is investment.

Firms face three types of capital adjustment frictions. (1) Orders for investment goods, denoted i^o_{jt}, are not delivered instantaneously. Instead, orders are delivered at the end of the period with probability q_t. (2) Capital adjustment is subject to fixed adjustment costs, which are reflected in the capital good price, p^E_t. This cost is random across firms reflecting stochastic overhead costs ξ. Each period, final good producers without outstanding orders take an iid draw of ξ from G, which determines the ξ-submarket on which they can hire an engineering firm. They decide to hire an engineer after observing ξ. Once an engineer is hired, ξ remains fixed until delivery. In addition, firms with an outstanding order incur a fixed cost γ when adjusting the order size. (3) Capital is subject to resale losses. A firm that sells part of its capital stock receives less than its purchase value. The resale loss of divestment is captured by function $\zeta(i^o)$. If the investment order i^o is negative, then $\zeta(i^o) = \bar{\zeta} i^o$, with $\bar{\zeta} \in [0,1]$, and else $\zeta(i^o) = i^o$. The resale loss is thus a fraction $(1-\bar{\zeta})$ of the divestment. Total investment expenditures (or divestment earnings) are defined by

$$ac_t(i^o_{jt}, \xi_{jt}) = p^E_t(\xi_{jt})\ \zeta(i^o_{jt}). \tag{4.12}$$

The presence of fixed capital adjustment costs and resale losses allow the model to match salient features of the investment rate distribution, see, e.g., Cooper and Haltiwanger (2006).

To formally state the dynamic firm problem, we distinguish between final good producers with and without outstanding orders. The idiosyncratic state of firms without an outstanding order is described by $(k_{jt}, x_{jt}, \xi_{jt})$. The associated cross-sectional probability distribution is denoted μ^V and defined for $S^V = \mathbb{R}^+ \times \mathbb{R}^+ \times \mathbb{R}^+$. Firms with an outstanding order have idiosyncratic state $(k_{jt}, i^o_{jt}, x_{jt}, \xi_{jt})$ and the associated distribution, μ^W, is defined for $S^W = \mathbb{R}^+ \times \mathbb{R} \times \mathbb{R}^+ \times \mathbb{R}^+$. The joint cross-sectional distribution is $\mu_t = (\mu^V_t, \mu^W_t)$ and defined for $S = S^V \times S^W$. The economy's aggregate state is denoted by $\mathbf{s}_t = (\mu_t, z_t, m_t, a_t)$. In the following, we drop time and firm indices and use $'$ notation to indicate subsequent periods. The value of a firm without an outstanding order is

$$V(k, x, \xi, \mathbf{s}) = \max \Big\{ V^O(k, x, \xi, \mathbf{s}), V^{NO}(k, x, \mathbf{s}) \Big\}, \tag{4.13}$$

where V^{NO} is the value of the firm without an outstanding order that makes no new order, and V^O is the value of the firm without an outstanding order that does make a new order,

$$V^{NO}(k, x, \mathbf{s}) = cf(k, x, \mathbf{s}) + \mathbb{E}\Big[Q(\mathbf{s}, \mathbf{s}')V((1-\delta)k, x', \xi', \mathbf{s}')\Big],$$
$$V^O(k, x, \xi, \mathbf{s}) = \max_{i^o \in \mathbb{R}} \Big\{ W(k, i^o, x, \xi, \mathbf{s}) \Big\}.$$

New orders are made to maximize the value of the firm with an outstanding order,

$$\begin{aligned}
W(k, i^o, x, \xi, \mathbf{s}) &= cf(k, x, \mathbf{s}) + \max \Big\{ W^A(k, x, \xi, \mathbf{s}), W^{NA}(k, i^o, x, \xi, \mathbf{s}) \Big\}, \qquad (4.14)\\
W^{NA}&(k, i^o, x, \xi, \mathbf{s})\\
&= q(\mathbf{s})\Big[-ac(i^o, \xi, \mathbf{s}) + \mathbb{E}\Big[Q(\mathbf{s}, \mathbf{s}')V\left((1-\delta)k + i^o, x', \xi', \mathbf{s}'\right)\Big]\Big]\\
&\quad + (1 - q(\mathbf{s}))\mathbb{E}\Big[Q(\mathbf{s}, \mathbf{s}')W\left((1-\delta)k, i^o, x', \xi, \mathbf{s}'\right)\Big],\\
W^A(k, x, \xi, \mathbf{s}) &= -\gamma w(\mathbf{s}) + \max_{i^{o\prime} \in \mathbb{R}} W^{NA}(k, i^{o\prime}, x, \xi, \mathbf{s}),
\end{aligned}$$

where W^A is the value of the firm with an outstanding order that readjusts the order, and W^{NA} is the value of the firm with an outstanding order that does not readjust it. An outstanding order i^o is delivered with probability q, and investment expenditures, ac, are payed upon delivery.[17] The extensive margin of the investment order decision is described by a threshold function $\hat{\xi}(k, x, \mathbf{s})$ that satisfies

$$V^O(k, x, \hat{\xi}(k, x, \mathbf{s}), \mathbf{s}) = V^{NO}(k, x, \mathbf{s}). \tag{4.15}$$

Adjustment is optimal whenever fixed adjustment costs $\xi < \hat{\xi}(k, x, \mathbf{s})$. Similarly, there exists

[17]This assumption is conservative. Under upfront payment, the cost of investment increases in time to build because of discounting. This would amplify the effects of supply chain disruptions.

a threshold $\hat{\gamma}(k, i^o, x, \xi, \mathbf{s})$ below which readjusting i^o is optimal. If $q(\mathbf{s}) = 1\ \forall \mathbf{s}$, the firm problem is the conventional problem with one period time to build, see, e.g., Khan and Thomas (2008).

4.4 Recursive Competitive Equilibrium

A *recursive competitive equilibrium* is a list of value functions $(V, W, V^S, J^S, V^E, J^E)$, policy functions $(C, L, \ell, \hat{\xi}, i^o, \hat{\gamma}, i^{o\prime})$, prices (w, p^S, p^E), market tightness (θ), and the cross-sectional distribution (μ) that satisfy the following.

(i) *Final good producers*: V and W solve (4.13)–(4.14) and $(\ell,\ i^o,\ \hat{\xi}, \hat{\gamma})$ are the associated policy functions.

(ii) *Engineers and suppliers*: V^S, J^S, V^E, J^E satisfy (4.4)–(4.5) and θ, p^S, p^E are the solutions to (4.6)–(4.7).

(iii) *Households*: C and L solve (4.1).

(iv) *Labor market clearing*:

$$L(\mathbf{s}) = L^Y(\mathbf{s}) + L^O(\mathbf{s}) + L^A(\mathbf{s}) \tag{4.16}$$

$L^Y(\mathbf{s})$ denotes labor demand by final good producers, $L^O(\mathbf{s})$ denotes overhead labor demand by engineers and suppliers, and $L^A(\mathbf{s})$ denotes labor demand for post-order adjustments. Formally,

$$L^Y(\mathbf{s}) = \int_S \ell(k, x, \mathbf{s}) d\mu, \tag{4.17}$$

$$L^O(\mathbf{s}) = \int_{S^V} \mathbb{1}\{\xi < \hat{\xi}(k, x, \mathbf{s})\}(1 + 1/\theta(\mathbf{s}))\xi d\mu^V + \int_{S^W} (1 + 1/\theta(\mathbf{s}))\xi d\mu^W, \tag{4.18}$$

$$L^A(\mathbf{s}) = \int_{S^W} \mathbb{1}\{\gamma < \hat{\gamma}(k, x, \mathbf{s})\}\gamma d\mu^W, \tag{4.19}$$

where $\mathbb{1}\{\cdot\}$ equals one if $\cdot$ is true and zero otherwise.[18]

(v) *Final good market clearing*:

$$C(\mathbf{s}) = Y(\mathbf{s}) - I(\mathbf{s}) \tag{4.20}$$

[18] Overhead labor demand depends on the mass of active engineers and suppliers. To compute the mass of active engineers, we need to compute the mass of outstanding orders. This allows us to compute the mass of active suppliers by multiplication with $1/\theta$.

$Y(\mathbf{s})$ denotes aggregate production of final good producers and $I(\mathbf{s})$ aggregate investment. Formally,

$$Y(\mathbf{s}) = \int_S zxk^\alpha \ell(k,x,\mathbf{s})^\nu d\mu, \tag{4.21}$$

$$I(\mathbf{s}) = \int_{S^V} \mathbb{1}\{\xi < \hat{\xi}(k,x,\mathbf{s})\} q(\mathbf{s})\zeta(i^o) d\mu^V + \int_{S^W} q(\mathbf{s})\zeta(i^o) d\tilde{\mu}^W, \tag{4.22}$$

where $\tilde{\mu}^W$ corresponds to μ^W after adjusting an outstanding order as described by $(\hat{\gamma}, i^{o\prime})$.

(vi) *Consistency*: The evolution of μ is consistent with the policy functions.

The capital supply side of the model is analytically tractable. The two zero conditions in (4.6) together with the solution to (4.7) jointly determine θ_t, p_t^E and p_t^S. In equilibrium, the investment expenditure (or divestment earning) is $p^E\zeta(i) = \zeta(i) + f(\xi)$, which consists of a unit price component and a fixed cost component, with the latter given by $f(\xi) = \frac{\xi w}{\phi q}$. The fixed cost component compensates engineers and suppliers for their overhead costs. Note that $f(\xi)$ increases in response to lower q because this raises the costs of capital good production.

The equilibrium tightness is $\theta_t = \frac{\phi}{1-\phi} a_t$. Hence, the order filling probability q_t unambiguously falls in negative shocks to matching efficiency m_t and in positive shocks to supplier costs a_t. A decline in matching efficiency lowers the probability that an engineer matches with an supplier to produce and fill its order. An increase in the supplier overhead cost lowers the relative entry of suppliers, which makes it less likely for engineers to match with suppliers. This lowers q_t and time to build lengthens.

5 Calibration and quantitative results

We calibrate the model. Supply chain disruptions have sizable macroeconomic effects.

5.1 Calibration and solution

We set the length of a period to a quarter and calibrate β to match an annual risk-free rate of 4%. The period utility function is additively separable, $U(C_t, L_t) = \log C_t - \psi L_t$. Linear disutility in labor follows from indivisible labor, see Hansen (1985) and Rogerson (1988). These preferences are common in the related literature, see, e.g., Khan and Thomas (2008) and Bloom et al. (2018). We target a share of hours worked of 1/3 to calibrate ψ.

Table 2: Calibrated parameters

Parameter		Value	Parameter		Value
Discount factor	β	0.99	Matching efficiency: mean	μ_m	0.546
Leisure preference	ψ	2.250	Matching efficiency: persistence	ρ_m	0.970
Bargaining power	ϕ	0.500	Matching efficiency: dispersion	σ_m	0.144
Output elasticity of capital	α	0.235	Firm productivity: persistence	ρ_x	0.970
Output elasticity of labor	ν	0.604	Firm productivity: dispersion	σ_x	0.062
Depreciation rate	δ	0.025	Aggr. productivity: persistence	ρ_z	0.979
Upper bound of fixed cost	$\bar{\xi}$	0.001	Aggr. productivity: dispersion	σ_z	0.007
Capital resale loss $(1-\bar{\zeta})$	$\bar{\zeta}$	0.850			

On the capital supply side of the model, we can generate the same movements in q_t through shocks to supplier costs a_t or shocks to matching efficiency m_t. Without loss of generality, we set $a_t = 1$ and focus on shocks to m_t. We assume symmetric Nash bargaining between engineers and suppliers, $\phi = 0.5$. This renders the delivery probability independent of the matching function elasticity η. We can leave η uncalibrated because it does not affect prices, policies, or value functions. To calibrate the process of matching efficiency, described by μ_m, ρ_m, and σ_m, we target the first and second moments of the backlog ratio series in Figure 1(a). The average backlog ratio is 5.5 months. To filter out the slow-moving time trend in the (quarterly) series, we use a low-frequency HP filter with $\lambda = 100,000$. Deviations from trend have a quarterly autocorrelation of 0.970 and a standard deviation of 0.144. In the model, we recompute the backlog ratio. Aggregate sales is aggregate investment in (4.22) and the aggregate order backlog in the model is

$$B(\mathbf{s}) = \int_{S^V} \mathbb{1}\{\xi < \hat{\xi}(k,x,\mathbf{s})\} ac(i^o(k,x,\mathbf{s}),\xi,\mathbf{s}) d\mu^V + \int_{S^W} ac(i^o,\xi,\mathbf{s}) d\mu^W. \tag{5.1}$$

To calibrate the parameters of the final good production technology, notably α, ν, ρ_x, σ_x, we use the estimates in Cooper and Haltiwanger (2006) based on the manufacturing plant-level Longitudinal Research Database (LRD). The original estimates in Cooper and Haltiwanger (2006) are at annual frequency and for a production function that can be thought of as maximizing out labor. We provide the details of how we transform their estimates in the notes of Table 4 in the Appendix. In general, the estimates in Cooper and Haltiwanger (2006) are well within the range of estimates in the literature, surveyed in Table 4. We set $\rho_z = 0.979$, $\sigma_z = 0.007$, and $\delta = 0.025$ as in King and Rebelo (1999).

Finally, we calibrate the capital adjustment cost parameters. G, the distribution of fixed capital adjustment costs ξ, is assumed to be uniform with zero lower bound and upper bound $\bar{\xi}$. This conforms with Khan and Thomas (2008) and Bachmann and Bayer (2013). To calibrate $\bar{\xi}$ as well as the resale loss parameter $\bar{\zeta}$, we target the empirical share of spike investment rates above 20% and below -20%. To be consistent with the calibration of α, ν, ρ_x, σ_x, we target the corresponding moments documented in Cooper and Haltiwanger (2006). They document an annual 19% share of plants with positive spikes and a 2% share of negative spikes. In the model, we aggregate the simulated quarterly data to annual frequency when computing shares of investment spikes. The two adjustment cost parameters allow us to match the shares of investment spikes. Intuitively, the fixed cost generates fat tails in the investment rate distribution. The resale loss strengthens the asymmetry between positive and negative spikes, beyond the asymmetry generated by deprecation. Table 3 shows that the calibrated model not only matches the two targeted moments of the investment rate distribution, but also closely matches a number of non-targeted moments. These non-targeted moments have been used in related work to target adjustment cost parameters, e.g., skewness and kurtosis in Bachmann and Bayer (2013). Furthermore, the calibrated $\bar{\zeta}$ implies a 15% resale loss of capital, which is well within the range of estimates in Cooper and Haltiwanger (2006) and Bloom (2009). We finally assume that re-adjusting an outstanding order before delivery is prohibitively costly, i.e. $\gamma > \hat{\gamma}$. This is motivated by the empirical evidence in Section 2, which suggests large costs of modifying outstanding orders.

Table 3: Moments of the investment rate distribution

	Model	Data
Targeted moments		
Positive spikes (LRD)	18.6%	19.1%
Negative spikes (LRD)	1.8%	1.8%
Non-targeted moments		
Persistence of investment rate (LRD)	0.016	-0.007
Productivity–investment rate correlation (LRD)	0.14	0.22
Skewness of investment rate (Census)	5.1	4.9
Kurtosis of investment rate (Census)	48.3	43.4

Notes: All moments relate to annual investment rates computed as I/K. LRD moments are from Cooper and Haltiwanger (2006) and Census moments are from Kehrig and Vincent (2016).

To solve the model, we first reduce the state space of the model and select approximation techniques. Second, we apply the solution algorithm proposed in Campbell (1998) and Reiter (2009). Conceptually, the idea is to combine global approximation methods with respect to the individual states, but local approximation methods with respect to the aggregate states of the model. The computational details are described in the Appendix.

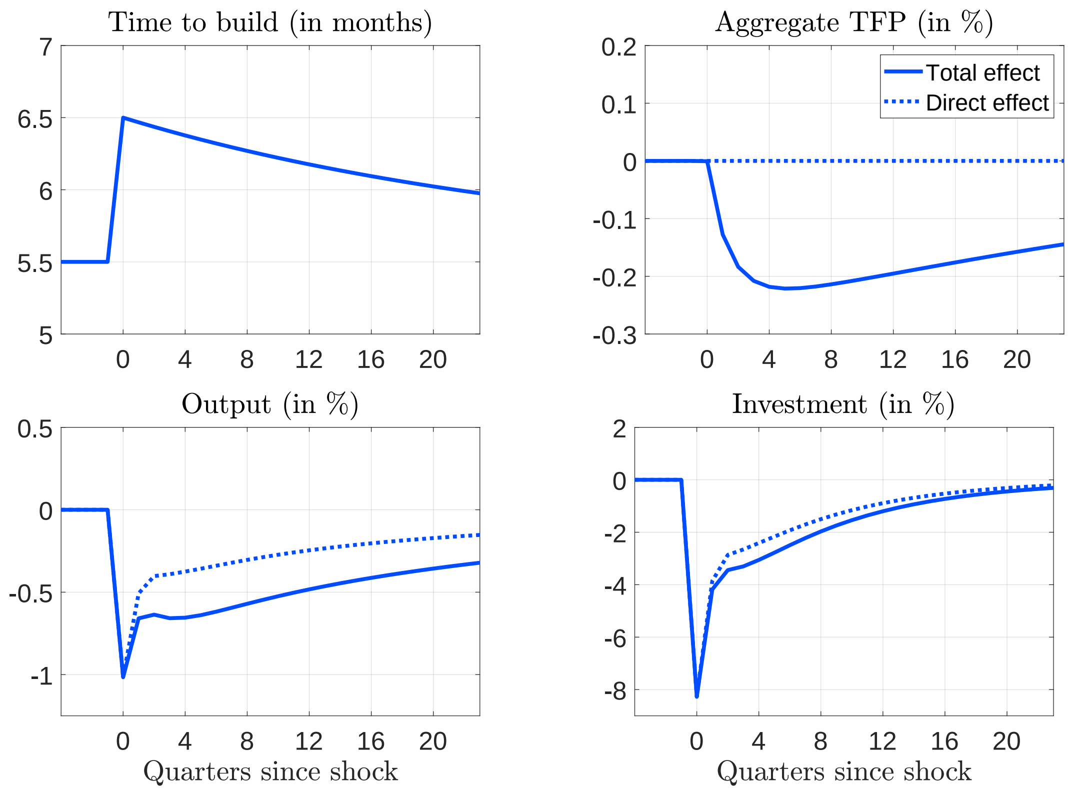
5.2 Macroeconomic effects of supply chain disruptions

Model impulse response functions in GE. We use the calibrated model to study the macroeconomic responses to a supply chain disruption that lengthens time to build from 5.5 months to 6.5 months on impact. The one-month increase corresponds to one standard deviation of the time to build series. Figure 2 shows that the shock causes sizable responses in output and investment. Investment – most directly affected by the disruption – falls by 8 percent on impact and remains 2 percent depressed two years later. Output falls by 1 percent on impact but converges back more slowly than investment. Measured aggregate TFP declines more gradually and reaches its trough only 5 quarters after the shock.

Two channels account for the total effect of supply chain disruptions. First, the *indirect channel*, which operates through capital misallocation. Second, the *direct channel*, which captures that longer time to build delays the delivery of outstanding orders and thereby reduces aggregate investment and output. In a model without firm heterogeneity, the direct effect remains operative, whereas the indirect effect disappears. We next disentangle these direct and indirect effects of supply chain disruptions. Since aggregate TFP only responds through the indirect channel, we isolate the direct channel by offsetting the endogenous TFP decline through a series of exogenous technology shocks such that TFP remains at its steady state level. These *direct effect* responses are shown as dotted lines in Figure 2. To understand the immediate responses of output and investment, the direct channel is central. The reason is that, on impact, the allocation of capital across producers cannot respond much: capital is predetermined and differences in idiosyncratic productivity are highly persistent. Few quarters after the disruption, capital misallocation becomes more important. About half of the output response is then due to the indirect effect.

The indirect effect in turn consists of two components. First, longer time to build worsens capital misallocation because firms invest less frequently. They do so because firms effectively face more uncertainty when making investment decisions. Figure 8 in the Appendix shows that the share of firms that do not sign a new order contract for capital goods goes up from 85.5% to 87%. Second, even if firms order and invest, the longer time delay between order and delivery implies that ex-post the investment is less well aligned with firm-level

Figure 2: Responses to a supply chain disruption



Notes: The figures show the general equilibrium impulse responses to a supply chain disruption that lengthens time to build by one month. 'Direct channel' denotes the impulse responses when aggregate TFP changes are eliminated through an offsetting series of aggregate technology (z) shocks. Aggregate TFP is computed as $TFP = \log(Y_t) - \alpha \log(K_t) - \nu \log(L_t)$.

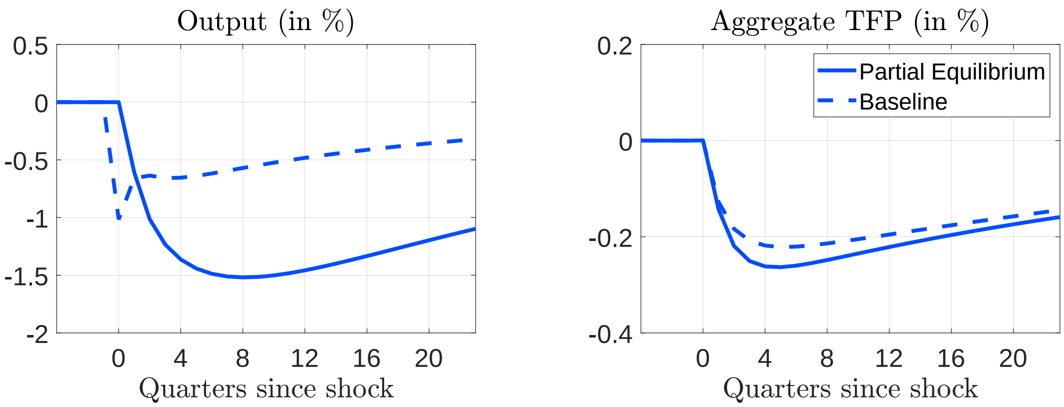
productivity. Figure 8 further shows that the order backlog increases after supply chain disruptions. Hence, the inflows to the backlog, new orders, fall more strongly than the outflows from the backlog, investment.

Partial equilibrium responses. We have so far studied the general equilibrium (GE) responses to supply chain disruptions. It is important to account for GE effects, because household consumption smoothing motives can substantially dampen the investment and output responses, see Khan and Thomas (2008). However, model misspecification may bias the GE effects. For example, our baseline model may be misspecified regarding preferences, expectation formation (e.g., learning about aggregate shocks), or the aggregate resource constraint (e.g., the model abstracts from international trade).

To shed light on the role of GE effects in the model, Figure 3 shows the responses of

GDP and aggregate TFP in partial equilibrium (PE). Different from the GE responses, wage and stochastic discount factor do not respond to the shock but remain at their steady state levels. While the baseline model is a closed-economy model, this setup may be justified as small open economy. For the US economy, truth is somewhere in between. In PE, the output response to supply chain disruptions is 50% larger compared to GE. In addition, the GDP response is now hump-shaped. The peak decline is attained only 9 quarters after the shock. The reason is that capital misallocation builds up gradually. Conversely, the sharp initial drop of GDP in the baseline model is due to price responses.

Figure 3: Partial equilibrium responses to a supply chain disruption

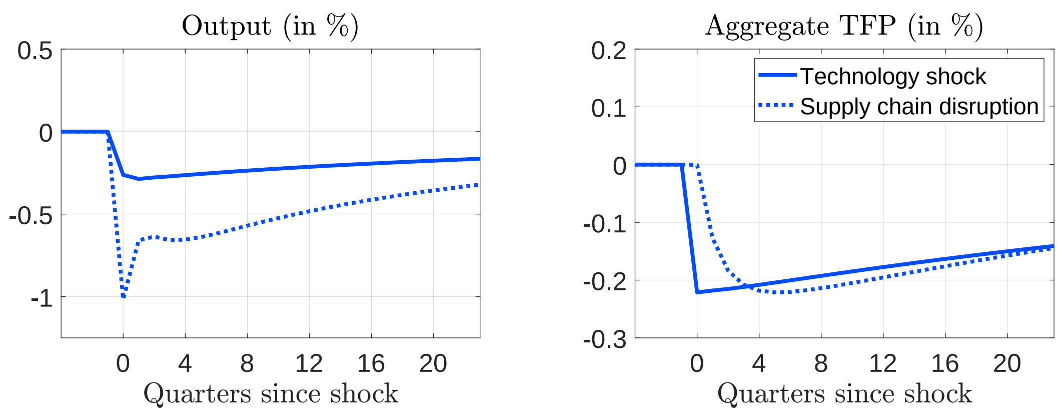


Notes: The figures show the partial equilibrium impulse responses to a supply chain disruption that lengthens time to build by one month.

The aggregate TFP response is similar in shape and only mildly amplified compared to the GE response. The time to build response is the same in GE and PE and that generates capital misallocation following the logic of the analytical framework in Section 3. Different from the analytical framework, in the full model the extensive margin of capital adjustment also responds to longer time to build. As longer time to build makes an investment project effectively more uncertain, some firms postpone orders for capital goods. This wait-and-see policy further contributes to capital misallocation and the aggregate TFP response. It is the extensive margin response, in which GE differs from PE. In GE, the consumption smoothing motive of households implies that there is less wait-and-see and relatively more extensive-margin capital adjustment.

Comparison with technology shocks. In Figure 4, we compare our baseline responses in Figure 2 with the responses to an exogenous aggregate technology shocks. The technology shock is scaled to attain a peak aggregate TFP response of 0.22% comparable to the supply chain disruption. The model propagates the technology shock through multi-period time to build. In the model with one-period time to build, GDP peaks when the shock hits and revert back to steady state afterwards. With multi-period time to build, the peak response is one quarter after the shock hits and the response is more persistent. It is almost by construction, that the GDP response to technology shocks is similar to the GDP response to a supply chain disruption purely from the indirect effect, i.e., the difference between total and direct effect in Figure 2.

Figure 4: Responses to a technology shock

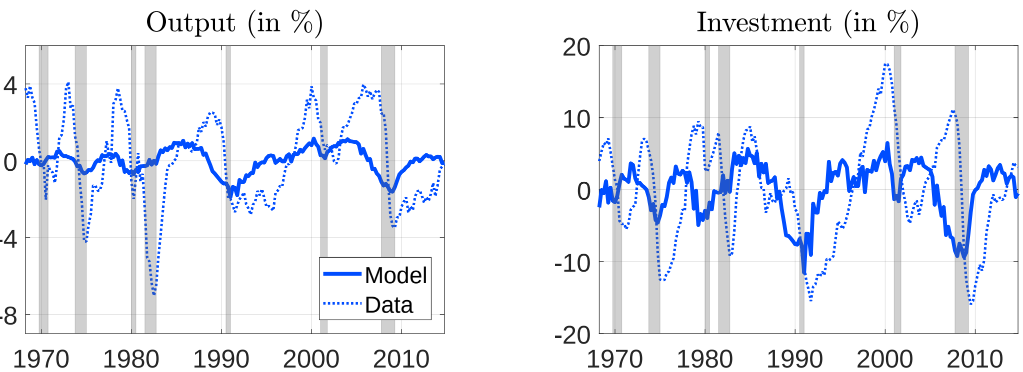


Notes: The figures show the general equilibrium impulse responses to an aggregate technology shock and to a supply chain disruption that lengthens time to build by one month.

Supply chain disruptions and post-war business cycles We next ask to what extent capital supply chain disruptions can help us understand post-war business cycles. We find that disruptions can explain up to half of the contraction in GDP during past recessions in the US. In particular, we consider the following exercise. We assume that movements in the empirical time to build series (observed from 1968 through 2015) are solely due to supply chain disruptions. This assumption likely give us an upper bound on the importance of supply chain disruptions. Through the lense of the model, we can back out the required series of disruption shocks and compute the implied series of GDP and investment. To be clear, we compute fluctuations in these series that are only driven by disruptions. To make the quarterly series comparable to the data, we HP filter both the simulated series and their empirical counterparts using the low-frequency filter employed in the calibration.

Panel (a) in Figure 5 plots the detrended empirical series of GDP and investment against their model counterparts. Three observations stand out. First, NBER recession periods (grey-shaded areas) correspond to periods in which supply chain disruptions cause below-trend output growth. Second, disruptions explain an important share of the observed business cycle variations. These shocks alone explains a drop in investments of 9-12% during the Great Recession and the early 1990s recession, compared to a drop of 15-16% in the data. For GDP, the model explains about half of the empirically observed drop during these two recessions. Third, the model suggests that disruptions alone tend to push the US economy into recession up to one year ahead of NBER recession periods.

Figure 5: Role of supply chain disruptions in understanding past business cycles



Notes: The above time series are computed matching the empirically observed (filtered) movements in time to build through supply chain disruptions and otherwise using the baseline model calibration. Grey-shaded areas indicate NBER recession dates.

6 VAR evidence

To gauge the macroeconomic effects of capital supply chain disruptions, we use a structural VAR model. Increases in time to build foreshadow large macroeconomic contractions.

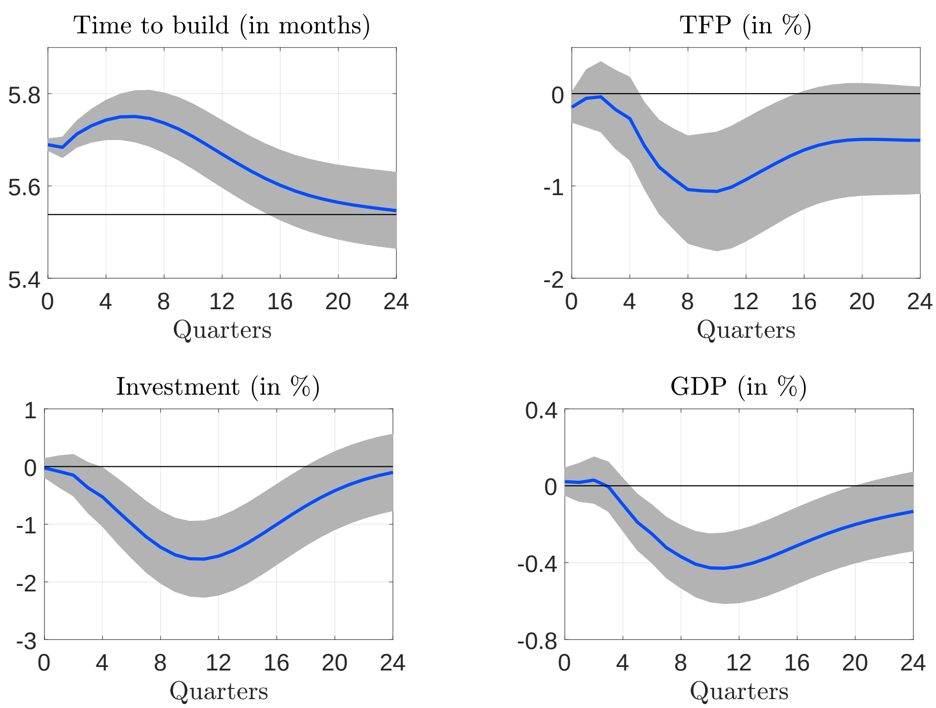
The baseline VAR model specification includes eight time series: time to build, real GDP, real consumption, real investment, consumer price, real wage, federal funds rate, and total factor productivity. All variables but the federal funds rate enter the VAR model in logs. We use data at quarterly frequency and cover 1968Q1 through 2014Q4. Time to build is the M3 backlog ratio, total factor productivity is from Fernald (2014), and the remaining macroeconomic series are sourced from FRED.[19] The baseline model specification is in levels

[19]The names of the FRED series we use are GDPC96 (*Real GDP*), DNDGRA3Q086SBEA (*Real Personal Consumption Expenditures: Nondurable goods*), B008RA3Q086SBEA (*Real Private Fixed Invest-*

with four lags and a linear time trend. To identify capital supply disruptions, we impose restrictions consistent with the business cycle model in Section 4: The only shock that affects time to build contemporaneously is a capital supply chain disruption. All other structural shocks may affect time to build through a one-period lag.

Figure 6 shows the impulse responses to a one standard deviation supply chain disruption. Time to build increases, while GDP and investment significantly fall. These responses are economically important: GDP falls by up to 0.4%, investment by up to 1.8%, and aggregate TFP by up to 1% within the first three years. The empirical results are robust in various dimensions. They are robust to a model in first-differences and without time trend, see Figure 10 in the Appendix. They are robust to the alternative identifying restriction that disruptions have a contemporaneous effect only on time to build, see Figure 11. Finally,

Figure 6: VAR impulse responses to a supply chain disruption



Notes: Solid, blue lines are the IRFs to a one standard deviation supply chain disruption. Shaded, gray areas show the associated 90% confidence intervals. The figures are based on the baseline eight-variate quarterly VAR model. The remaining four IRFs are shown in Figure 9 of the Appendix.

ment: Nonresidential), CPI, AHETPI/CPI (*Average Hourly Earnings of Production and Nonsupervisory Employees: Total Private; deflated by CPI*), FEDFUNDS (*Effective Federal Funds Rate*). The results are robust against using total consumption and total investment.

they are robust to a monthly VAR model, see Figure 13. The monthly model includes time to build, industrial production, consumption, CPI, real wages, FFR, average hours worked, and employment.

Moreover, we explore variations of the baseline model, in which we respectively add or replace variables that are potentially important. The variables added are Jurado et al. (2015)'s macro uncertainty, the relative price of investment goods, Gilchrist and Zakrajšek (2012)'s credit spread, Fernald (2014)'s factor utilization, total inventories from the M3 survey, and the S&P500 index. In addition, we replace TFP by utilization-adjusted TFP from Fernald (2014). Figure 11 shows that the responses of time to build, TFP, investment, and GDP are robust across model variations. Figure 12 shows the IRFs of the added variables. Uncertainty rises after a capital supply disruption, which may reflect the increased uncertainty in the firm's investment planning problem under longer time to build. Both the relative investment price and credit spreads do not respond significantly. This suggests that disruptions do not pick up investment-specific technology shocks or financial shocks.

7 Conclusion

This paper makes an original contribution to the business cycle literature by studying the role of fluctuations in time to build. We establish that time to build is countercyclical and provide micro evidence that time to build lengthens in response to capital supply chain disruptions. Motivated by this evidence, we develop a dynamic stochastic general equilibrium model. In the model, fluctuations in time to build are driven by supply chain disruptions. Calibrated to US data, we find that such disruptions to capital supply have sizable macroeconomic effects. A shock that lengthens time to build by one month depresses GDP by up to one percent.

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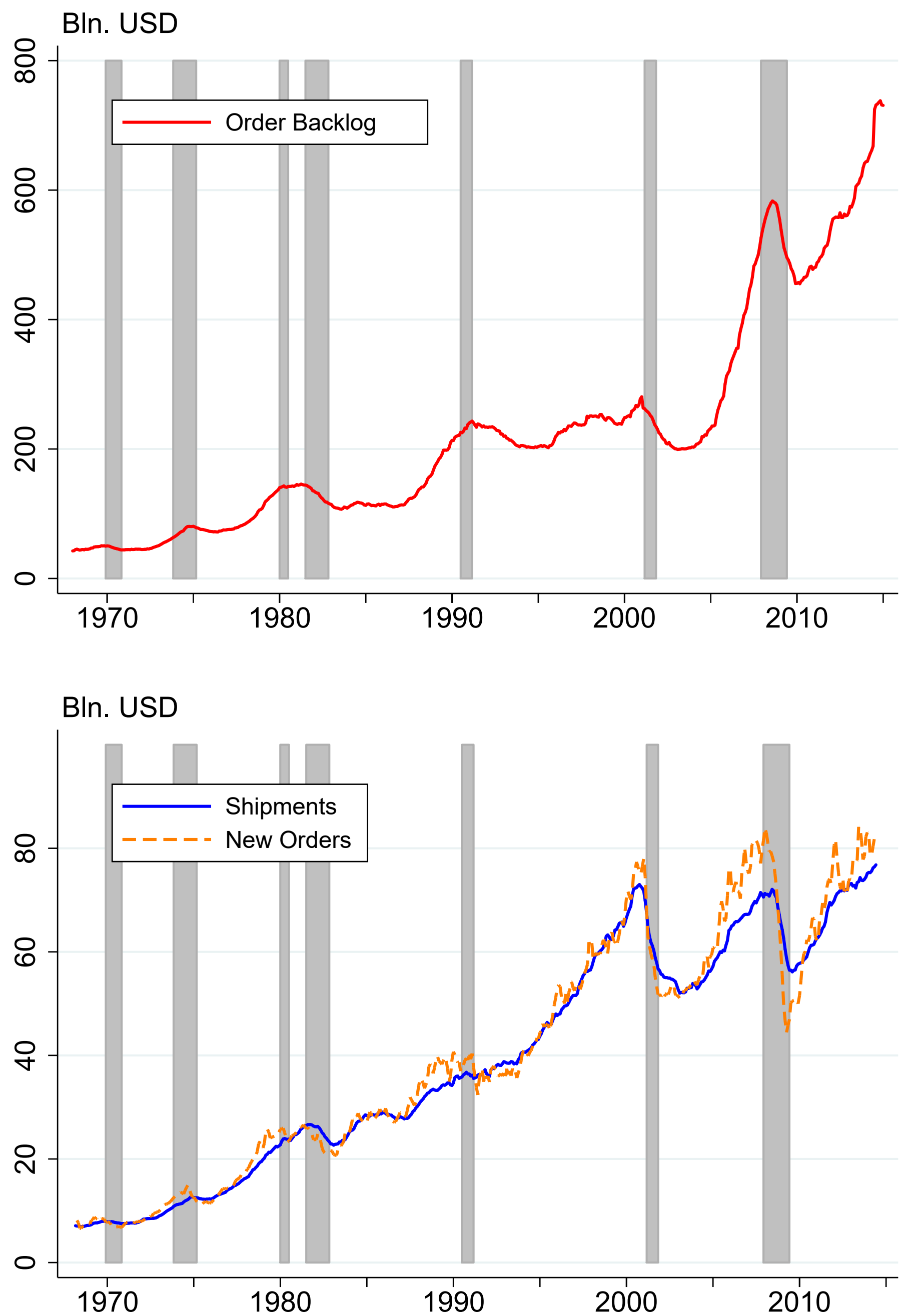
Appendix

A Order backlog, shipment, and new orders

Figure 7: Aggregate order backlog, shipments, and new orders



Notes: All series refer to the non-defense equipment goods sector from M3 data and are expressed in nominal values. Shaded, gray areas indicate NBER recession dates.

B Production technology and the aggregate TFP of time to build

The literature knows a wide range of estimates for α, ν, ρ_x, and σ_x in Sections 3 and 4. The following will provide a short survey of estimates in the literature. Estimates differ in the underlying micro data, which implies differences in time period, frequency (quarterly or annual), unit of observation (plants or firms), and scope (public or private firms, manufacturing or all sectors). Further differences lie in the calibration or estimation strategy. One approach is to estimate all parameters directly from the micro data, another approach is indirect by targeting moments of the investment rate distribution. The first five columns of Table 4 summarize prominent estimates in the literature with additional details provided in the table notes.

A pervasive result across estimates is (i) the high persistence of firm/plant-level profitability shocks, and (ii) the large variance of these shocks. In comparison, typical estimates of aggregate productivity shocks are at least an order of magnitude smaller. Both (i) and (ii) are important for the misallocation mechanism. If firm-level profitability shocks are volatile but transitory, changes in time to build will not induce any factor misallocation. Conversely, if firm-level shocks are persistent but little volatile, being able to respond to them a month sooner or later will have a little impact at the aggregate level.

Table 4: Aggregate TFP loss when time to build lengthens from 5 to 6 months

Calibration	α	ν	ρ_x	σ_x	TFP loss
data source: annual manufacturing plant-level LRD data, 1972-1998					
Cooper and Haltiwanger (2006)	0.235	0.604	0.970	0.062	0.21%
Khan and Thomas (2013)	0.270	0.600	0.901	0.068	0.30%
data source: annual manufacturing plant-level ASM/CMF data, 1972-2009					
Kehrig (2015)	0.290	0.650	0.622	0.138	1.14%
data source: quarterly firm-level Compustat data, 1973-2012					
Gilchrist et al. (2014)	0.255	0.595	0.900	0.150	0.23%
data source: quarterly firm-level IRS data, 1997-2010					
Winberry (2016)	0.210	0.640	0.940	0.026	0.04%

Notes: A period is a quarter and we increase τ from 5/3 to 6/3 quarters. The TFP loss is formally defined as $\text{TFP}_{5/3} - \text{TFP}_{6/3}$. Whenever the original calibration is at annual frequency, I impute quarterly persistence ρ_x using $\rho_{x,\text{annual}}^{1/4}$, and quarterly dispersion σ_x accordingly. Cooper and Haltiwanger (2006) estimate the revenue production function $y_{jt} = \tilde{x}_{jt} k_{jt}^{\theta}$. The estimated $\theta = \alpha/(1-\nu) = 0.592$ together with the estimated labor cost share $a_L = \nu/(\alpha+\nu) = 0.72$ pins down α and ν. Considering the production function as maximizing out labor, then $x_{jt} = \tilde{x}_{jt}^{1-\nu}$, which allows me to impute σ_x. Khan and Thomas (2013) assume $\nu = 0.60$ following Cooley and Prescott (1995), and calibrate $\alpha = 0.256$ to match an aggregate capital-to-output ratio of 2.3. They calibrate ρ_x and σ_x by targeting the share of LRD plants with spike investments, investment inaction, and investment dispersion. Kehrig (2015) estimate all parameters from the data while including six-digit industry fixed effects. Gilchrist et al. (2014) assume a 30% capital cost share and estimate the remaining parameters from the data. Winberry (2016) assumes $\nu = 0.64$, $\alpha + \nu = 0.85$, and targets moments of the investment rate distribution to calibrate ρ_x and σ_x.

C Solution algorithm

The recursive competitive equilibrium is not computable, because the solution depends on the infinite-dimensional distribution μ and its law of motion. Instead, we approximate the equilibrium by adopting the algorithm proposed in Campbell (1998) and Reiter (2009). The general idea is to use global approximation methods with respect to the individual states, but local approximation methods with respect to the aggregate states. We solve the steady state of the model using projection methods and perturb the model locally around the steady state to solve for the model dynamics in response to aggregate shocks. Compared to the Krusell-Smith algorithm, see Krusell et al. (1998), the perturbation approach does not require simulating the model dynamics in order to update the parameters of the forecasting rules. Further it can handle a large number of aggregate shocks.

In this section, we first show how to simplify the equilibrium conditions. Second, we explain in detail how to apply the Campbell-Reiter algorithm to our model.

C.1 Simplified final good firm problem

To solve the model in a computationally efficient way, we rewrite the problem of the final good firm. To save on notation, we first drop the aggregate state $\mathbf{s}$ and instead index functions that depend on the aggregate state by time t subscripts. Second, we transform the firm problem. Instead of i^o, the investment order, we let firms choose k^o, the new capital stock upon delivery. Computationally, this transformation has the advantage that we can use the same grid for k^o as for k, and this grid is naturally tighter than the one for i^o. To leave the firm problem unchanged, k^o needs to evolve over time to guarantee the implicitly defined investment order i^o remains unchanged. Using the identity, $i^o = k^o + (1-\delta)k$, the evolution of k^o over time (conditional on no delivery) is given by

$$k^{o\prime} = k^o - \delta(1-\delta)k.$$

Third, we simplify the investment expenditure function. In terms of k^o, we have

$$ac_t(k, k^o, \xi) = \zeta(k^o - (1-\delta)k) + f_t(\xi).$$

All adjustment costs including the latter term, which captures fixed adjustment costs, is paid upon delivery. All that matters for the firm, however, is the expected present value of this fixed cost, which we denote by $fac_t\ \xi$. Note that fac_t can be solved recursively using

$$fac_t = q_t \frac{w_t}{\phi q_t} + (1-q_t)\mathbb{E}_t Q_{t,t+1} fac_{t+1},$$

where $\mathbb{E}_t$ denotes the expectation with respect to aggregate state $\mathbf{s}_{t+1}$ conditional on $\mathbf{s}_t$. Fourth, we redefine the firm value functions such that the expectation with respect to idiosyncratic productivity is not computed within the maximization problem. This raises computational efficiency and tends to smooth the value functions. More precisely, we define

$$\tilde{V}_t(k,x,\xi) = \mathbb{E}_{x'}\mathbb{E}_{\xi'}V_t(k,x',\xi'), \quad \tilde{W}_t(k,k^o,x,\xi) = \mathbb{E}_{x'}W_t(k,k^o,x',\xi),$$

where $\mathbb{E}_x$ ($\mathbb{E}_\xi$) denotes the expectation with respect to x' (ξ') conditional on x (ξ). Finally, we simplify the firm problem in equations (4.13)–(4.14),

$$\begin{aligned}
&\tilde{V}_t(k,x) = \mathbb{E}_{x'}\mathbb{E}_{\xi'}\max\Big\{V_t^O(k,x') - fac_t\xi', V_t^{NO}(k,x')\Big\},\\
&V_t^{NO}(k,x) = cf_t(k,x) + \mathbb{E}_t Q_{t,t+1}\Big[\tilde{V}_{t+1}((1-\delta)k,x)\Big],\\
&V_t^O(k,x) = \max_{k^o\in\mathbb{R}^+}\Big\{W_t(k,k^o,x)\Big\},\\
&W_t(k,k^o,x) = cf_t(k,x)\\
&\qquad + q_t\Big[-\zeta(k^o-(1-\delta)k) + \mathbb{E}_t\Big[Q_{t,t+1}\tilde{V}_{t+1}(k^o,x)\Big]\Big]\\
&\qquad + (1-q_t)\mathbb{E}_t\Big[Q_{t,t+1}\tilde{W}_{t+1}((1-\delta)k, k^o-\delta(1-\delta)k,x)\Big]\Big],\\
&\tilde{W}_t(k,k^o,x) = \mathbb{E}_{x'}W_t(k,k^o,x').
\end{aligned}$$

This allows us to compute the extensive margin adjustment policy in closed form,

$$\hat{\xi}_t(k,x) = \frac{\tilde{V}_t^O(k,x) - \tilde{V}_t^{NO}(k,x)}{fac_t}.$$

In line with above reformulation of the firm problem, we redefine μ_t^V as the cross-sectional distribution of firms without outstanding orders over idiosyncratic states (k,x) and μ_t^W as the distribution of firms with outstanding orders over (k,k^o,x). It holds that $\mu_t = (\mu_t^V,\mu_t^W)$.

C.2 Approximations

We approximate the AR(1) process of idiosyncratic productivity using Tauchen's algorithm. We denote the discrete grid points of x by $x_1,...,x_{n_x}$ consisting of n_x grid points and the transition probability from state x_j to state $x_{j'}$ one period later by $\pi_x(x_{j'}|x_j)$. Next, we approximate the firm value function in arguments k and k^o using the collocation method. Φ

denotes basis functions in matrix representation and c denotes vectors of coefficients

$$\begin{aligned}\tilde{V}_t(k,x) \simeq& \Phi^V(k,x)c_t^V,\\ \tilde{W}_t(k,k^o,x) \simeq& \Phi^W(k,k^o,x)c_t^W.\end{aligned}$$

The approximations are exact at the n_k collocation nodes $k_1,...,k_{n_k}$ and $k_1^o,...,k_{n_k}^o$. We choose the same collocation nodes for k and k^o. We use cubic B-splines to approximate the firm value functions. This does not only have the advantage of being computationally fast, but also conditional on the coefficients we know the Jacobian in closed form. In particular, we can write down the optimality condition for intensive margin capital adjustment (k_t^o) as

$$q_t\zeta(k_t^o-(1-\delta)k) = q_t\mathbb{E}_tQ_{t,t+1}\Phi_k^V(k_t^o,x)c_{t+1}^V + (1-q_t)\mathbb{E}_tQ_{t,t+1}\Phi_{k^o}^W((1-\delta)k,k_t^o,x)c_{t+1}^W,$$

where $\Phi_k^V = (\partial\Phi^V)/(\partial k)$ and $\Phi_{k^o}^W = (\partial\Phi^W)/(\partial k^o)$. To render the infinite-dimensional distribution μ_t tractable, we approximate it with a discrete histogram. That is, μ_t measures the share of firms for each discrete combination of capital stock k_{i_1}, outstanding order $k_{i_2}^o$ (both correspond to the collocation nodes), and productivity x_j.

C.3 Labor demand

Note that labor demand depends on labor used in production and overhead labor used by engineers and suppliers. Labor used in production is

$$L_t^Y = \sum_{i_1,i_2,j}\mu_t(k_{i_1},k_{i_2},x_j)(\nu/w_t)^{1/(1-\nu)}(z_tx_j)^{1/(1-\nu)}k_{i_1}^{\alpha/(1-\nu)}.$$

Computing the overhead labor demand is difficult because it depends on the distribution of engineers over submarkets ξ, which in turn depends on past decisions of final good firms to make an order in submarket ξ, formally $\hat{\xi}_{t-j}(k,x)\ \forall j \geq 1$. In the original setup of the final good firm this information was contained in distribution μ_t^W, but, after the above simplifications, μ^W does not contain ξ anymore. We propose a simple remedy to this problem. Denote by ξ_t^{av} the average ξ across all outstanding orders (including new and old orders). Then, labor demand of engineers is simply

$$L_t^{O,E} = \left(\int d\mu_t^W + \int \mathbb{1}\{\xi < \hat{\xi}_t\}dG(\xi)d\mu_t^V\right)\ \xi_t^{av}.$$

Since delivery is state-independent, next period's ξ_{t+1}^{av} only depends on $\hat{\xi}_{t+1}$ and today's ξ_t^{av}. It does, however, not depend on the distribution of engineers over the (k,k^o,x) space or the duration of search. Formally, we have

$$\begin{aligned}
\xi_{t+1}^{av} =& \frac{(1-q_t)\int \xi_t^{av} d\mu_t^W + \int \xi \mathbb{1}\{\xi < \hat{\xi}_{t+1}\} dG(\xi) d\mu_{t+1}^V}{(1-q_t)\int d\mu_t^W + \int \mathbb{1}\{\xi < \hat{\xi}_{t+1}\} dG(\xi) d\mu_{t+1}^V} \\
=& \frac{(1-q_t)\sum_{i_1,i_2,j} \mu_t^W(k_{i_1},k_{i_2},x_j)\xi_t^{av} + \sum_{i,j} \mu_t^V(k_i,x_j)\frac{\bar{\xi}}{2}\left(\frac{\hat{\xi}_t(k_i,x_j)}{\bar{\xi}}\right)^2}{(1-q_t)\sum_{i_1,i_2,j} \mu_t^W(k_{i_1},k_{i_2},x_j) + \sum_{i,j} \mu_t^V(k_i,x_j)\left(\frac{\hat{\xi}_t(k_i,x_j)}{\bar{\xi}}\right)},
\end{aligned}$$

and in steady state

$$\bar{\xi}^{av} = \left(\sum_{i,j} \mu^V(k_i,x_j)\frac{\bar{\xi}}{2}\left(\frac{\hat{\xi}(k_i,x_j)}{\bar{\xi}}\right)^2\right) \Big/ \left(\sum_{i,j} \mu^V(k_i,x_j)\left(\frac{\hat{\xi}(k_i,x_j)}{\bar{\xi}}\right)\right).$$

In equilibrium, the overhead labor demand of suppliers is simply a factor $1/\theta$ of the engineers' overhead labor demand. Thus, total overhead labor demand is given by

$$L_t^O = L_t^{O,E}(1+1/\theta).$$

C.4 Campbell-Reiter algorithm

Using the preceding approximation and simplification steps, the model equilibrium is described by the following non-linear equations:

$$\Phi^V(k,x)c_t^V = \mathbb{E}_{x'}\mathbb{E}_{\xi'} \max\left\{V_t^O(k,x') - fac_t\xi', V_t^{NO}(k,x')\right\} \tag{C.1}$$

$$V_t^{NO}(k,x) = cf_t(k,x) + \mathbb{E}_t Q_{t,t+1}\Phi^V((1-\delta)k,x)c_{t+1}^V$$

$$V_t^O(k,x) = W_t(k,k_t^o,x)$$

$$\begin{aligned}
W_t(k,k^o,x) = & cf_t(k,x) \\
& + q_t\Big[\zeta(k^o-(1-\delta)k) + \mathbb{E}_t Q_{t,t+1}\Phi^V(k^o,x)c_{t+1}^V\Big] \\
& + (1-q_t)\Big[\mathbb{E}_t Q_{t,t+1}\Phi^W((1-\delta)k, k^o - \delta(1-\delta)k, x)c_{t+1}^W\Big]
\end{aligned}$$

$$\Phi^W(k,k^o,x)c_t^W = \mathbb{E}_{x'}W_t(k,k^o,x') \tag{C.2}$$

$$fac_t = \frac{w_t}{\phi} + (1-q_t)\mathbb{E}_t Q_{t,t+1} fac_{t+1} \tag{C.3}$$

$$\hat{\xi}_t(k,x) = (V_t^O(k,x) - V_t^{NO}(k,x))/fac_t$$

$$cf_t(k,x) = (1-\nu)\left(\nu/w_t\right)^{\nu/(1-\nu)}\left(z_t x\right)^{1/(1-\nu)} k^{\alpha/(1-\nu)}$$

$$q_t = m_t(\phi/(1-\phi))^{\eta-1}$$

$$q_t\zeta(k^o_t-(1-\delta)k)=q_t\mathbb{E}_tQ_{t,t+1}\Phi^V_k(k^o_t,x)c^V_{t+1}+(1-q_t)\mathbb{E}_tQ_{t,t+1}\Phi^W_{k^o}((1-\delta)k_t,k^o_t,x)c^W_{t+1} \tag{C.4}$$

$$\begin{aligned}\mu^V_{t+1}(k_{i'},x_{j'}) &= \sum_{i,j}\pi_x(x_{j'}|x_j)\mu^V_t(k_i,x_j)[\omega^{V,V,O}_t(i,i',j)+\omega^{V,V,NO}_t(i,i',j)] \\ &\quad+\sum_{i_1,i_2,j}\pi_x(x_{j'}|x_j)q_t\mu^W_t(k_{i_1},k^o_{i_2},x_j)\omega^{W,V}_t(i_1,i_2,i',j)\end{aligned} \tag{C.5}$$

$$\begin{aligned}\mu^W_{t+1}(k_{i'_1},k_{i'_2},x_{j'}) &= \sum_{i,j}\pi_x(x_{j'}|x_j)\mu^V_t(k_i,x_j)\omega^{V,W}_t(i,i'_1,i'_2,j) \\ &\quad+\sum_{i_1,i_2,j}\pi_x(x_{j'}|x_j)\mu^W_t(k_{i_1},k_{i_2},x_j)\omega^{W,W}_t(i_1,i_2,i'_1,i'_2,j)\end{aligned} \tag{C.6}$$

$$Y_t=\sum_{i_1,i_2,j}\mu_t(k_{i_1},k_{i_2},x_j)\,(\nu/w_t)^{\nu/(1-\nu)}\,(z_tx_j)^{1/(1-\nu)}k_{i_1}^{\alpha/(1-\nu)}$$

$$\begin{aligned}I_t &= \sum_{i,j}\mu^V_t(k_i,x_j)G(\hat{\xi}_t(k_i,x_j))q_t\zeta(k^o_t-(1-\delta)k_i) \\ &\quad+\sum_{i_1,i_2,j}\mu^W_t(k_{i_1},k^o_{i_2},x_j)q_t\zeta(k^o_{i_2}-(1-\delta)k_{i_1})\end{aligned}$$

$$C_t=Y_t-I_t$$

$$\begin{aligned}L_t &= \sum_{i_1,i_2,j}\mu_t(k_{i_1},k_{i_2},x_j)(\nu/w_t)^{1/(1-\nu)}(z_tx_j)^{1/(1-\nu)}k_{i_1}^{\alpha/(1-\nu)} \\ &\quad+\left(\sum_{i_1,i_2,j}\mu_t(k_{i_1},k_{i_2},x_j)+\sum_{i,j}\mu^V_t(k_i,x_j)\frac{\hat{\xi}_t(k_i,x_j)}{\bar{\xi}}\right)\ \xi^{av}_t\ (1+1/\theta)\end{aligned}$$

$$\xi^{av}_{t+1}=\frac{(1-q_t)\sum_{i_1,i_2,j}\mu_t(k_{i_1},k_{i_2},x_j)\xi^{av}_t+\sum_{i,j}\mu^V_t(k_i,x_j)\frac{\bar{\xi}}{2}\left(\frac{\hat{\xi}_t(k_i,x_j)}{\bar{\xi}}\right)^2}{(1-q_t)\sum_{i_1,i_2,j}\mu_t(k_{i_1},k_{i_2},x_j)+\sum_{i,j}\mu^V_t(k_i,x_j)\left(\frac{\hat{\xi}_t(k_i,x_j)}{\bar{\xi}}\right)} \tag{C.7}$$

$$w_t=U_L(C_t,L_t)/U_C(C_t,L_t) \tag{C.8}$$

$$Q_{t,t+1}=\beta U_C(C_{t+1},L_{t+1})/U_C(C_t,L_t) \tag{C.9}$$

$$\log(m_{t+1})=(1-\rho^m)\log(\mu^m)+\rho^m\log(m_t) \tag{C.10}$$

$$\log(z_{t+1})=\rho^z\log(z_t) \tag{C.11}$$

With the following auxiliary equations for the law of motion of the distribution:

$$\omega^{V,V,O}_t(i,i',j)=\begin{cases}G(\hat{\xi}_t(k_i,x_j))q_t\frac{k_{i'}-k^o_t(k_i,x_j)}{k_{i'}-k_{i'-1}} & \text{if}\quad k^o_t(k_i,x_j)\in[k_{i'-1},k_{i'}] \\ G(\hat{\xi}_t(k_i,x_j))q_t\frac{k^o_t(k_i,x_j)-k_{i'}}{k_{i'+1}-k_{i'}} & \text{if}\quad k^o_t(k_i,x_j)\in[k_{i'},k_{i'+1}] \\ 0 & \text{else}\end{cases}$$

$$\omega_t^{V,V,NO}(i,i',j)=\begin{cases}[1-G(\hat{\xi}_t(k_i,x_j))]\frac{k_{i'}-(1-\delta)k_i}{k_{i'}-k_{i'-1}} & \text{if} \quad (1-\delta)k_i\in[k_{i'-1},k_{i'}]\\ [1-G(\hat{\xi}_t(k_i,x_j))]\frac{(1-\delta)k_i-k_{i'}}{k_{i'+1}-k_{i'}} & \text{if} \quad (1-\delta)k_i\in[k_{i'},k_{i'+1}]\\ 0 & \text{else}\end{cases}$$

$$\omega_t^{V,W}(i,i_1',i_2',j)=\begin{cases}G(\hat{\xi}_t(k_i,x_j))(1-q_t)\frac{k_{i_1'}-(1-\delta)k_i}{k_{i_1'}-k_{i_1'-1}}\frac{k_{i_2'}-k_t^o(k_i,x_j)}{k_{i_2'}-k_{i_2'-1}}\\ \qquad \text{if} \quad k_t^o(k_i,x_j)\in[k_{i_2'-1},k_{i_2'}] \quad \text{and} \quad (1-\delta)k_i\in[k_{i'-1},k_{i'}]\\ G(\hat{\xi}_t(k_i,x_j))(1-q_t)\frac{(1-\delta)k_i-k_{i_1'}}{k_{i_1'+1}-k_{i_1'}}\frac{k_{i_2'}-k_t^o(k_i,x_j)}{k_{i_2'}-k_{i_2'-1}}\\ \qquad \text{if} \quad k_t^o(k_i,x_j)\in[k_{i_2'-1},k_{i_2'}] \quad \text{and} \quad (1-\delta)k_i\in[k_{i'},k_{i'+1}]\\ G(\hat{\xi}_t(k_i,x_j))(1-q_t)\frac{k_{i_1'}-(1-\delta)k_i}{k_{i_1'}-k_{i_1'-1}}\frac{k_t^o(k_i,x_j)-k_{i_2'}}{k_{i_2'+1}-k_{i_2'}}\\ \qquad \text{if} \quad k_t^o(k_i,x_j)\in[k_{i_2'},k_{i_2'+1}] \quad \text{and} \quad (1-\delta)k_i\in[k_{i'-1},k_{i'}]\\ G(\hat{\xi}_t(k_i,x_j))(1-q_t)\frac{(1-\delta)k_i-k_{i_1'}}{k_{i_1'+1}-k_{i_1'}}\frac{k_t^o(k_i,x_j)-k_{i_2'}}{k_{i_2'+1}-k_{i_2'}}\\ \qquad \text{if} \quad k_t^o(k_i,x_j)\in[k_{i_2'},k_{i_2'+1}] \quad \text{and} \quad (1-\delta)k_i\in[k_{i'},k_{i'+1}]\\ 0 \quad \text{else}\end{cases}$$

$$\omega_t^{W,V}(i_1,i_2,i',j)=\begin{cases}q_t\frac{k_{i'}-k_{i_2}}{k_{i'}-k_{i'-1}} & \text{if} \quad k_{i_2}\in[k_{i'-1},k_{i'}]\\ q_t\frac{k_{i_2}-k_{i'}}{k_{i'+1}-k_{i'}} & \text{if} \quad k_{i_2}\in[k_{i'},k_{i'+1}]\\ 0 & \text{else}\end{cases}$$

$$\omega_t^{W,W}(i_1,i_2,i_1',i_2',j)=\begin{cases}(1-q_t)\frac{k_{i_1'}-(1-\delta)k_{i_1}}{k_{i'}-k_{i_1'-1}} & \text{if} \quad (1-\delta)k_{i_1}\in[k_{i_1'-1},k_{i_1'}] \quad \text{and} \quad i_2'=i_2\\ (1-q_t)\frac{(1-\delta)k_{i_1}-k_{i_1'}}{k_{i_1'+1}-k_{i_1'}} & \text{if} \quad (1-\delta)k_{i_1}\in[k_{i_1'},k_{i_1'+1}] \quad \text{and} \quad i_2'=i_2\\ 0 & \text{else}\end{cases}$$

Given n_k collocation nodes and n_x discrete grid points of x, the labeled equations (C.1)–(C.11) are $n_f\equiv 2n_k^2n_x+3n_kn_x+6$ in number. We consider the labeled equations as main equations in defining the model equilibrium. All other unlabeled equations are auxiliary equations. We organize the n_f labeled equations in

$$\mathbb{E}_t[f(\mathbf{x}_t,\mathbf{x}_{t+1},\mathbf{y}_t,\mathbf{y}_{t+1})]=0, \tag{C.12}$$

where $\epsilon_t=(\epsilon_t^m,\epsilon_t^z)\in\mathbb{R}^2$ denotes the vector of aggregate shocks. $\mathbf{x}_t$ denotes predetermined state variables and $\mathbf{y}_t$ denotes non-predetermined state variables (control variables)

$$\mathbf{x}_t = [\mu_t; \log(\xi_t^{av}); \log(m_t); \log(z_t)] \in \mathbb{R}^{n_x}, \quad n_x \equiv n_k^2 n_x + n_k n_x + 3 \tag{C.13}$$

$$\mathbf{y}_t = [c_t^V; c_t^W; \log(k_t^o); \log(Q_{t,t+1}); \log(fac_t); \log(w_t)] \in \mathbb{R}^{n_y}, \quad n_y \equiv n_k^2 n_x + 2n_k n_x + 3. \tag{C.14}$$

In the general case, the model solution is given by

$$\mathbf{y}_t = g(\mathbf{x}_t, \zeta), \tag{C.15}$$

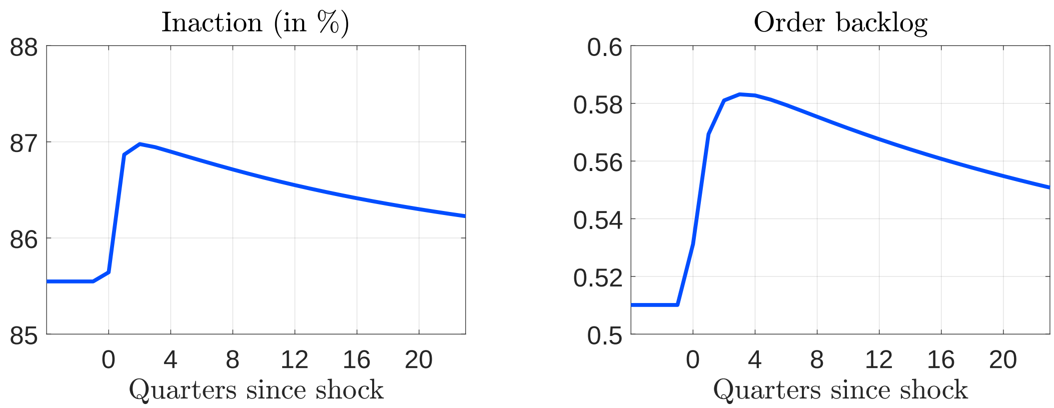
$$\mathbf{x}_{t+1} = h(\mathbf{x}_t, \zeta) + \zeta\tilde{\sigma}\epsilon_{t+1}, \tag{C.16}$$

where ζ is the perturbation parameter and $g : \mathbb{R}^{n_x} \times \mathbb{R}^+ \to \mathbb{R}^{n_y}$ and $f : \mathbb{R}^{n_x} \times \mathbb{R}^+ \to \mathbb{R}^{n_x}$. The exogenous shocks are collected in $\epsilon_{t+1} \in \mathbb{R}^{n_\epsilon}$, and $\tilde{\sigma} \in \mathbb{R}^{n_x \times n_\epsilon}$ attributes shocks to the according equations and scales them (by σ^m, σ^z). To solve the two policy functions, we use a first-order approximation. We follow the perturbation algorithm in Schmitt-Grohe and Uribe (2004). This requires us to compute the Jacobians of function f (locally) around steady state. The (non-stochastic) steady state is defined as $f(\bar{\mathbf{x}}, \bar{\mathbf{x}}, \bar{\mathbf{y}}, \bar{\mathbf{y}}) = 0$. Thus, we first solve the steady state and then use finite-differences to compute the Jacobian matrices of f with respect to its four arguments. The algorithm in Schmitt-Grohe and Uribe (2004) also allows us to check for existence and uniqueness of a model solution.

The costliest part in the computation relates to the $2n_k^2 n_x$ equations associated with μ^W and c^W. In principle, we could reduce the number of equations by computing the policy function k_t^o from other control variables, without including it as a control variable. However, solving the model involves root-finding in every perturbation, which is (a) computationally expensive, and (b) potentially unstable.

D Further model results

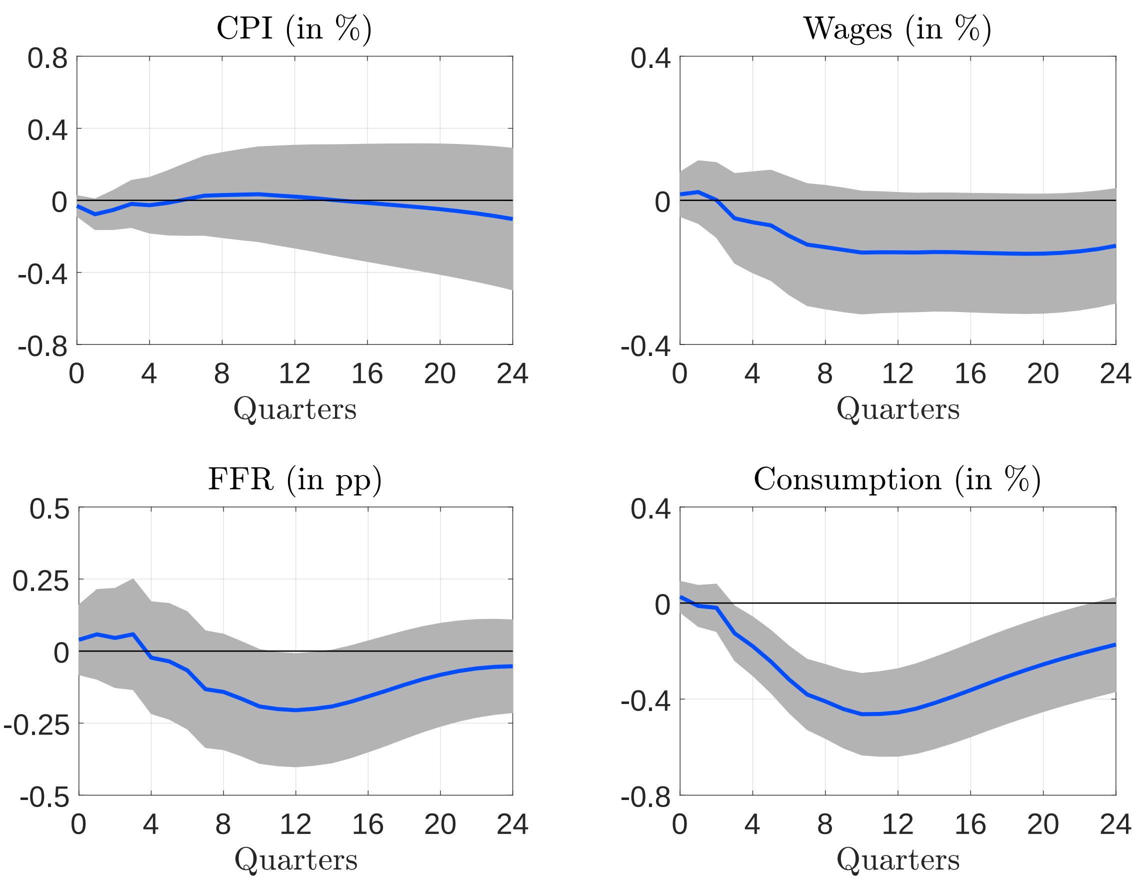
Figure 8: Further GE responses to a supply chain disruption



Notes: The figures show the general equilibrium impulse responses to a supply chain disruption that lengthens time to build by one month.

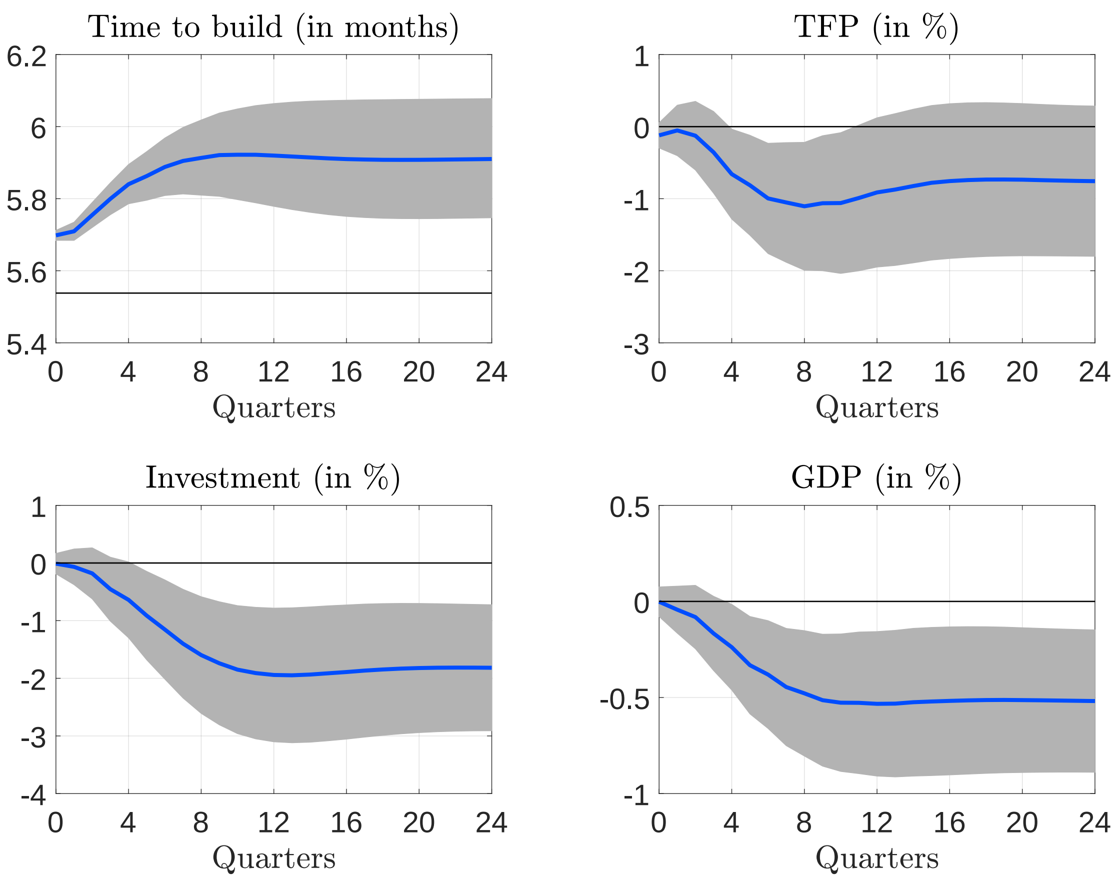
E SVAR robustness and additional results

Figure 9: Baseline VAR model: remaining IRFs to a capital supply disruption



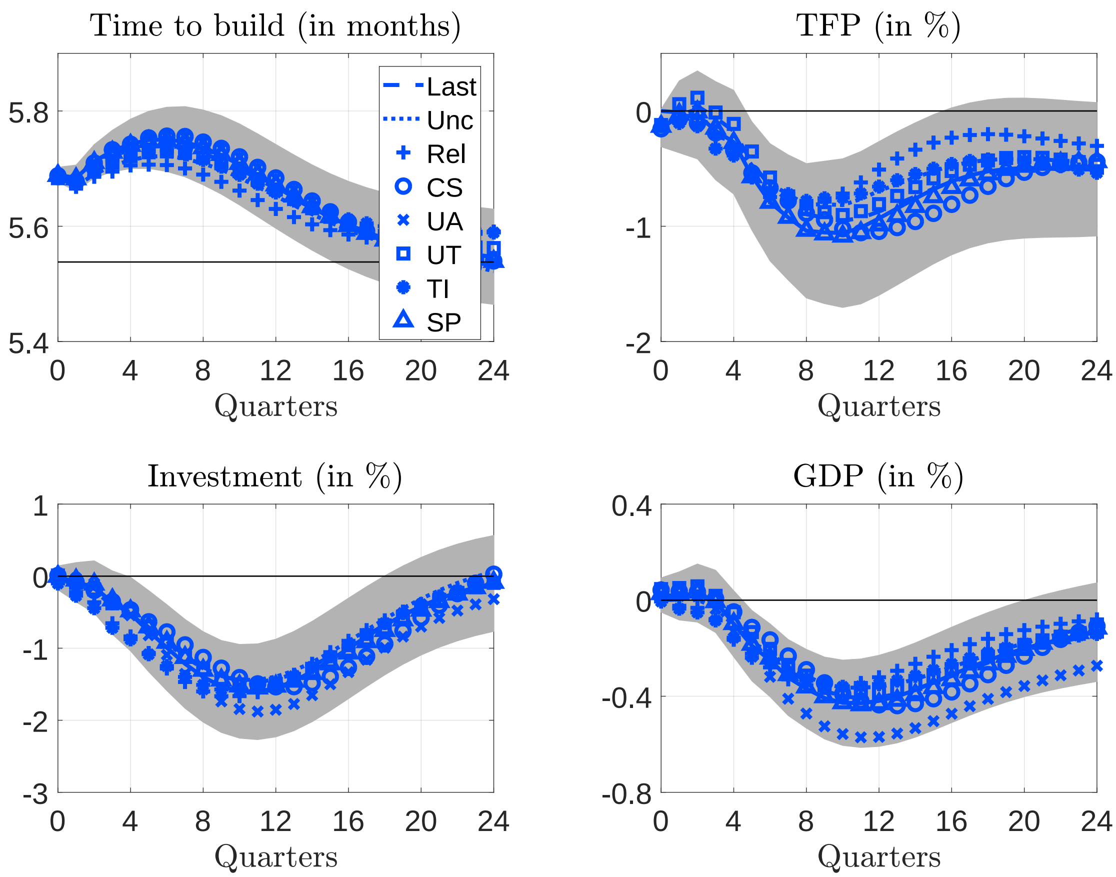
Notes: Solid, blue lines show (selected) IRFs to a one-standard deviation capital supply disruption shock. Shaded, gray areas show the associated 90% confidence intervals. The figures are based on the baseline eight-variate quarterly VAR model. The other four IRFs are shown in Figure 6.

Figure 10: *First-differenced* VAR model: IRFs to a capital supply disruption



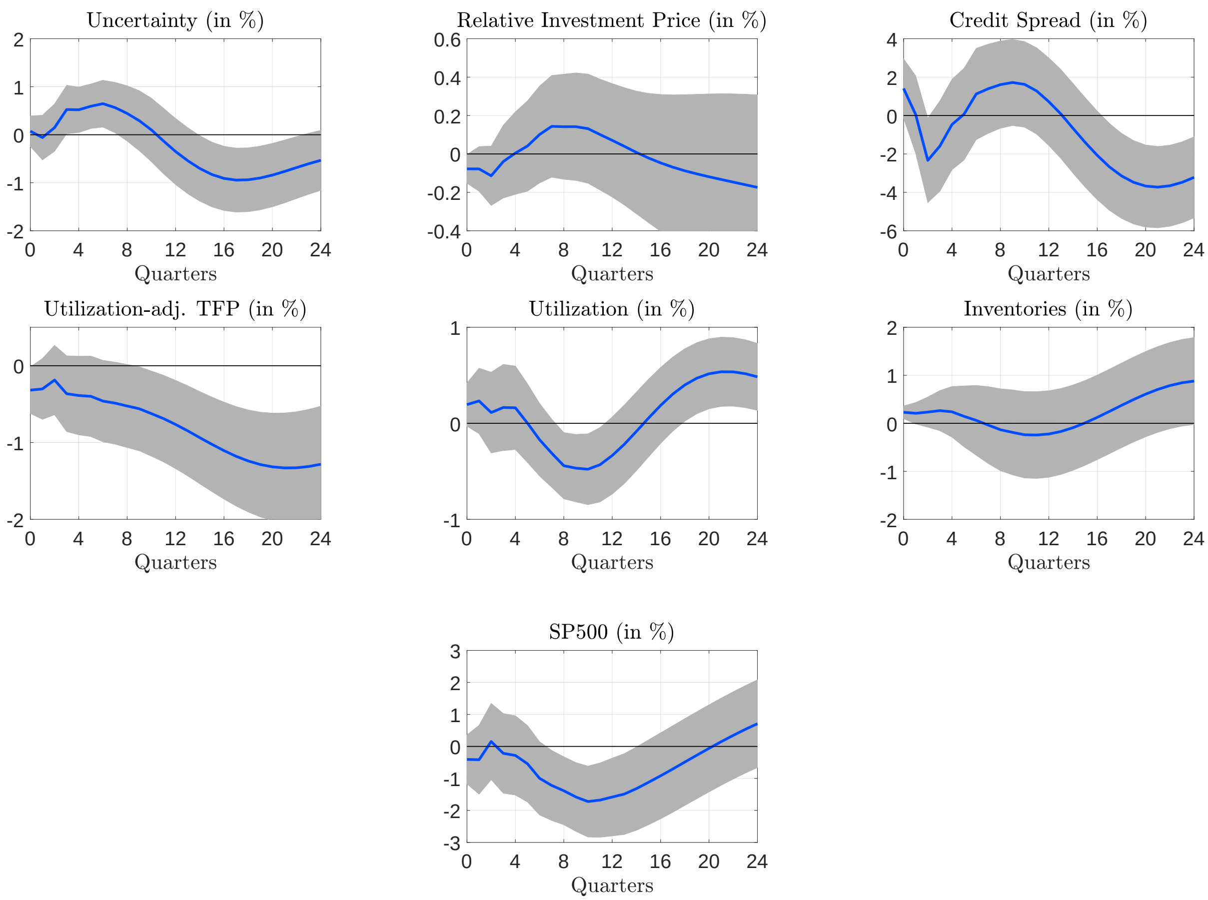
Notes: Solid, blue lines show (selected) cumulative IRFs to a one-standard deviation capital supply disruption shock. Shaded, gray areas show the associated 90% confidence intervals. The figures are computed from an eight-variate quarterly VAR model in first differences (without a time trend).

Figure 11: *Variations* of baseline VAR model: IRFs to a capital supply disruption



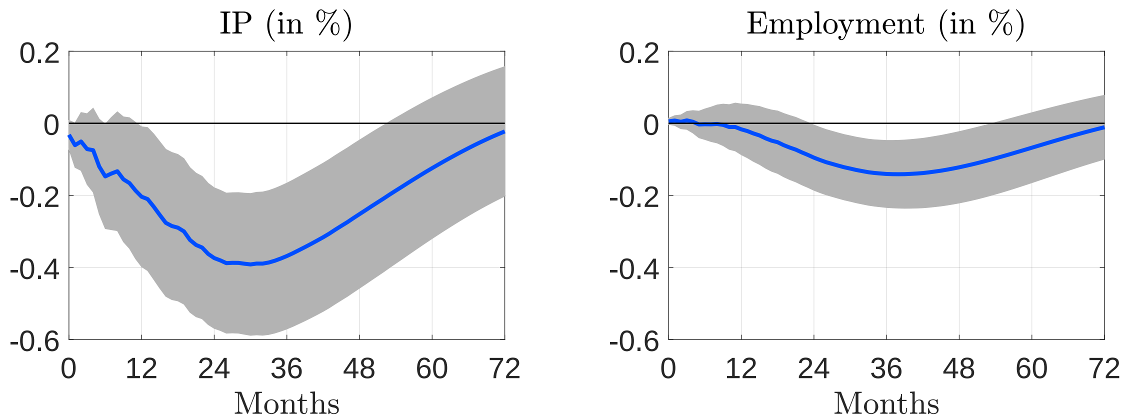
Notes: Solid, blue lines show (selected) IRFs to a one-standard deviation capital supply disruption shock, and shaded, gray areas show the associated 90% confidence intervals, under the baseline model. The figure includes further impulse responses under variations of the structural VAR model. *'Last'* identifies capital supply disruptions by ordering time to build last; *'Unc'* adds Jurado et al. (2015)'s macro uncertainty; *'Rel'* adds the relative price of investment goods; *'CS'* adds Gilchrist and Zakrajšek (2012)'s credit spread; *'UA'* replaces TFP by Fernald (2014)'s utilization-adjusted TFP; *'UT'* adds Fernald (2014)'s factor utilization; *'TI'* adds total inventories from the M3 survey; *'SP'* adds the S&P500 index.

Figure 12: *Additional* IRFs to a capital supply disruption

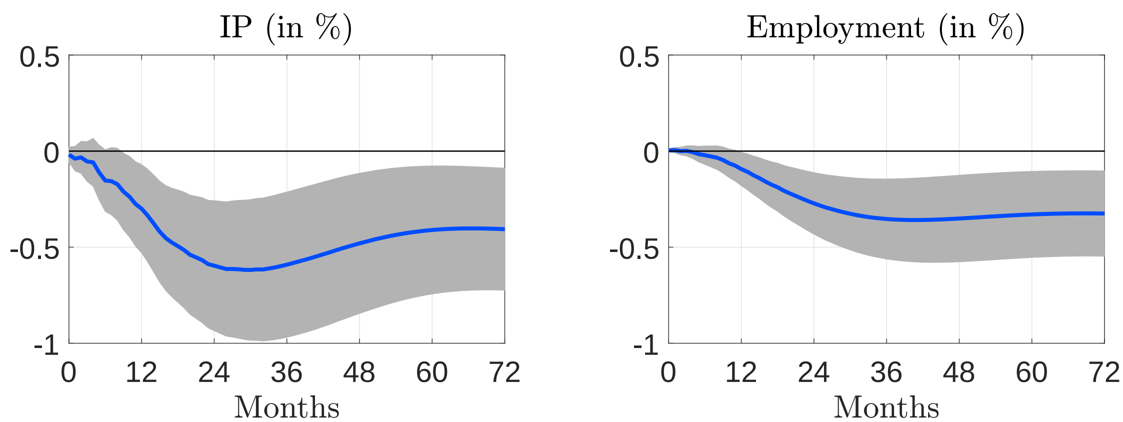


Notes: Solid, blue lines show (selected) IRFs to a one-standard deviation capital supply disruption shock. Shaded, gray areas show the associated 90% confidence intervals. The IRFs are based on variations of the baseline VAR model, which add one variable, respectively. The single exception is utilization-adjusted TFP from Fernald (2014), which replaces TFP in the baseline model. The variables added are Jurado et al. (2015)'s macro uncertainty, the relative price of investment goods, Gilchrist and Zakrajšek (2012)'s credit spread, Fernald (2014)'s factor utilization, total inventories from the M3 survey, and the S&P500 index.

Figure 13: *Monthly* VAR model: IRFs to a capital supply disruption



(a) Variables in levels



(b) Variables in first differences

Notes: Solid, blue lines show (selected) IRFs to a one-standard deviation capital supply disruption shock. Shaded, gray areas show the associated 90% confidence intervals. The IRFs in panel (a) are based on an eight-variate monthly VAR model with 12 lags and linear time trend. The variables included are time to build, industrial production, consumption, CPI, real wages, FFR, average hours worked, and employment (all in logs except FFR). Panel (b) shows cumulative IRFs based on the same eight-variate monthly VAR model with 12 lags but estimated in first differences (without time trend).