Supply Chain Shortages, Large Firms' Market Power, and Inflation

Francesco Franzoni Mariassunta Giannetti Roberto Tubaldi *

August 16, 2024

Abstract

Following supply chain disruptions, large firms are less impacted by the resulting shortages. Motivated by this new evidence, we develop a framework to explore the consequences of supply chain shortages on industrial structure. The main prediction is that large firms gain a competitive advantage over smaller competitors. Consistent with this conjecture, following supply chain shortages, the larger firms in an industry experience higher market share, profitability, markups, and stock returns, and smaller cost increases. Shortages are associated with higher price hikes in ex-ante more concentrated industries. This mechanism can explain up to 23% of U.S. inflation during 2021.

*Franzoni is with U.S.I Lugano, the Swiss Finance Institute, and CEPR. Giannetti is with the Stockholm School of Economics, the Swedish House of Finance, CEPR, and ECGI. Tubaldi is with BI Norwegian Business School. We thank Viral Acharya, John Asker, Alessandro Barbarino, Olivier Blanchard, Adrien D'Avernas, Itamar Drechsler, Tim Eisert, Laurent Frésard, Peter Kondor, Alexandra Niessen-Ruenzi, Elena Paltseva, Chad Syverson, David Thesmar, Luana Zaccaria, and conference and seminar participants at the Barcelona School of Economics Summer Forum Workshop on Financial Shocks, Channels, and Economic Outcomes, the CEPR Paris Symposium, the ESCB Research Network on Challenges for Monetary Policy Transmission in a Changing World (ChaMP) Inaugural Conference, the Swedish Researchers in Industrial Economics (SweRIE) Workshop, the Bank of Italy, the Universidad Carlos III de Madrid, BI Norwegian Business School, LUISS, CSEF, University of Bologna, Università Ca' Foscari (Venezia), Montpellier Business School, and Queen Mary University for comments and discussions. Giannetti acknowledges financial support from the Jan Wallander and Tom Hedelius Foundation and the Karl-Adam Bonnier Foundation. Emails: francesco.franzoni@usi.ch, mariassunta.giannetti@hhs.se, roberto.tubaldi@bi.no

1 Introduction

Over the decades since globalization took off, companies have developed complex value chains, which, for a long time, have decreased costs and generated higher profits (Antràs and Chor, 2022). More recently, geopolitical tensions and the Covid-19 pandemic have attracted policymakers' attention to the risks underlying this global economic network and the severe repercussions that supply chain shortages and disruptions can have on economic activity. However, despite the growing evidence on the importance of supply chain shocks, we know rather little about how firms respond to supply chain shortages and the implications of individual firm behavior for industry structure and macroeconomic outcomes. Specifically, how different firms can navigate supply chain shortages and how these shocks impact the competitive structure of the industry remain understudied questions.

This paper investigates the impact of supply chain shortages on firm performance and industrial structure. We conjecture that supply chain shortages increase production costs because firms cannot utilize the optimal mix of production inputs. Whether supply chain shortages ultimately impact an industry structure depends on the exposure of different companies to the shocks.

A priori, the direction of the effect is not obvious. To the extent that the largest firms in an industry, which we label superstars in line with prior literature (Autor, Dorn, Katz, Patterson, and Van Reenen, 2020, Gutiérrez and Philippon, 2019), have more complex and international supply chains (Ersahin, Giannetti, and Huang, 2024), they could be more negatively affected and shrink relatively to their smaller competitors when supply chain shortages occur. On the other hand, large firms could suffer less from supply chain shortages because they have more resilient supply chains and more bargaining power to obtain preferential treatment from their suppliers. If this is the case, supply chain shortages could lead to a larger increase in production costs for relatively smaller firms. If supply chain shortages finally benefit large firms, we could observe higher concentration and markups, especially in industries featuring a few superstar companies competing with smaller firms.

We provide evidence consistent with the latter conjecture. Using Bills of Lading data, we show that superstar firms obtain larger deliveries than the smaller customers of the same supplier when supply chain shortages occur. The competitive advantage of superstar firms is further reinforced by their more diversified supply chains. Moreover, their suppliers are often very large and less negatively affected by supply chain shortages. We observe that, consequently, the cost advantage of large companies over their within-industry competitors increases when supply chain shortages occur.

Based on this motivating evidence, we explore, with the help of a stylized model, how supply chain shortages affect the industry equilibrium. Consistent with the model's predictions, we find that when upstream industries experience backlogs, the largest firms in an industry acquire market share, experience smaller increases in production costs, increase their markups, and experience higher profitability and stock returns than their competitors. Our findings are robust to considering cost shocks and heterogeneity in pass-through rates between firms with different market power.

The changes in industry equilibrium we describe can be driven by more resilient supply chains and suppliers favoring their larger customers, which consequently are less negatively affected by the input shortages. As a complementary mechanism, it is also possible that superstar firms, being more reliable suppliers, experience positive increases in demand at the expense of their competitors when supply chain shortages disrupt deliveries. These two channels reinforce each other and are not mutually exclusive. If superstar firms benefit from input rationing due to supply chain shortages, their advantage arises from the shortages; on the other hand, if the anticipation of shortages prompts a reallocation of demand towards larger firms, also in this case superstar firms are the ultimate beneficiaries. Thus, as we show in our theoretical framework, demand shocks and supply shocks have similar equilibrium implications.

While demand and supply shocks triggered by a supply chain shortage have equivalent equilibrium implications, a separate concern is that a positive demand shock only affecting superstar firms may be the ultimate driver of supply chain disruptions. We provide two pieces of evidence to rule out this possibility. First, we find that when supply chain shortages occur, ex ante more concentrated industries experience smaller increases in aggregate sales. This finding is inconsistent with a demand shock affecting large firms and driving the shortages because we should observe a relative increase in quantity sold in ex ante more concentrated industries, which by definition are dominated by large firms. The finding instead supports our hypothesis that increased market power leads to less output being produced. Second, we construct an instrument to capture supply chain shortages arising from port congestion. This instrument allows us to exclude that demand shocks experienced by superstar firms drive supply chain shortages and to show that our results are robust.

Overall, it appears that supply chain shortages can lead to increased market share and profits for large firms, which experience an improvement in their competitive advantage. Because of the shortages, the difference in marginal costs between superstar firms and their competitors increases, and consequently, superstar firms face less competition. This mechanism can explain why superstar firms can increase prices well above costs in response to supply chain bottlenecks. Thus, higher prices do not merely reflect higher costs, the so-called pass-through effect, but they result from an improvement in the competitive position of superstar firms.

At the aggregate level, the enhanced competitive advantage of superstar firms could help explain the inflationary impact of supply chain shortages. We show that consistent with our conceptual framework, ex ante more concentrated industries, where superstar firms play a more prominent role, experience larger increases in concentration and drops in sales when supply chain shortages occur. As a result, these industries experience higher inflation.

Aggregating across all industries, we estimate that the proposed mechanism can explain up to 23% of the inflation that materialized in 2021 during the Covid-19 pandemic recovery in the U.S. Thus, our evidence provides a micro-foundation for the findings of recent macroeconomic research arguing that supply chain shortages have been an important driver of inflation during the Covid-19 period (Bernanke and Blanchard, 2023, 2024).

We contribute to several strands of the literature. First, a growing body of work highlights an increase in market power driven by the largest firms (De Loecker and Eeckhout, 2018). It is heatedly debated whether these firms, often labeled superstars, are more efficient (Autor, Dorn, Katz, Patterson, and Van Reenen, 2020) or enjoy oligopolistic rents (Gutiérrez and Philippon, 2021, Grullon, Larkin, and Michaely, 2019). It is also unclear whether the outperformance of superstar firms is driven by the mismeasurement of intangible capital (Ayyagari, Demirguc-Kunt, and Maksimovic, 2023). Existing studies have mostly documented secular trends and their effects on the labor market and wage growth (Autor, Dorn, Katz, Patterson, and Van Reenen, 2020). We study the effects of supply chain shortages on superstar firms and their competitors. Since we are interested in superstars' responses to relatively short-lived shocks, we are agnostic on the determinants of their superstar status. The mechanism through which superstar firms' markups and market power increase because of supply chain shortages is similar to that that Eeckhout and Veldkamp (2022) highlight in the context of data: Superstar firms' competitive advantage increases because they can produce at lower costs relative to their competitors.

Second, we contribute to a growing literature studying the channels through which microeconomic frictions can affect aggregate supply and inflation. Most of the literature highlights different channels through which monetary and real shocks affect firms' costs and, consequently, prices (Barth and Ramey, 2001). Chevalier and Scharfstein (1996) propose that binding financial constraints lead firms to reduce capacity and increase prices during recessions and following monetary policy tightening (see also Antoun de Almeida, 2015, for empirical evidence). Importantly, since small firms are more subject to financial constraints, this channel implies that profit margins increase more for small firms and has, therefore, opposite implications to the mechanism we propose. Drechsler, Savov, and Schnabl (2023) show how a severe credit crunch caused by regulation Q led to a negative supply shock, which can explain stagflation in the seventies. Acharya, Crosignani, Eisert, and Eufinger (2023b) highlight how zombie lending contributes to excess capacity and deflation. We contribute to this literature by highlighting the interplay of market structure, production networks, and supply chain shortages.

More closely related to us, contemporaneous work by Acharya, Crosignani, Eisert, and Eufinger (2023a) shows that heightened household inflation expectations allowed firms to pass cost shocks to prices and that the effect was particularly strong for high market power firms. We provide a complementary channel and show that when supply chain shortages occur, the market power of the largest firms in an industry increases. Consequently, during the Covid-19 pandemic recovery, inflation has increased in concentrated industries, which are those in which supply chain shortages affect firms more heterogeneously.

Finally, we contribute to the literature showing how shocks propagate over production networks and affect economic outcomes (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012, Barrot and Sauvagnat, 2016, Carvalho, Nirei, Saito, and Tahbaz-Salehi, 2021). Macro studies in this line of research highlight that import price increases and supply chain disruptions constrained the Covid-19 pandemic recovery and fostered inflation (e.g., Kemp, Portillo, and Santoro, 2023, Hansen, Toscani, and Zhou, 2023, Di Giovanni, Kalemli-Özcan, Silva, and Yildirim, 2023). Evidence on the extent to which marginal cost pass-through increased firms' markups is mixed (Gagliardone, Gertler, Lenzu, and Tielens, 2023). Differently from these studies, we highlight how changes in firms' competitive environments contributed to the inflation spiral. Our channel is distinct from cost pass-through which should be larger in competitive industries. We show that in industries dominated by a few large firms, differences in competitiveness between firms increase because of supply chain shortages. Markups thus increase because of a less competitive environment.

2 Data

Our analysis relies on various firm-level and macro data that we combine to gauge firm performance and behavior, supply chain shortages, and industry-level inflation. Below we describe our data sources in turn.

Firms and their supply chains We obtain firm-level financial information from Worldscope. Our sample covers 18,969 firms in 83 countries across 62 2-digit SIC industries. We construct measures of firms' market shares, profitability, and markups, which we introduce in the empirical analysis. Our sample period is 2010-2021, constrained by the availability of our proxy for supply chain shortages, described below. Table 1 provides detailed variable definitions, while Table 2 presents summary statistics.

Consistent with previous literature that considers the largest companies within an industry (De Loecker and Eeckhout, 2018, Autor, Dorn, Katz, Patterson, and Van Reenen, 2020), superstar firms are defined as those ranking in the top 10% of the sales distribution within a 2-digit SIC-code industry in the prior year for the universe of international firms. Thus, while the identity of superstars could change over time, as Autor, Dorn, Katz, Patterson, and Van Reenen (2020) note, their status is very persistent. Specifically, the probability of being a superstar in year t given that a firm was a superstar in year $t-1$ is 94%, and it is 91% if the firm was a star in year $t-2$.

Because our analysis relies on Worldscope, we only observe listed companies that tend to be the largest in the economy. Thus, the companies in our sample are more homogeneous than the population of firms in a country, which makes it harder to find a differential effect of supply chain shortages between large and relatively smaller firms, the relationship that we intend to study.

Finally, we obtain the main customers and suppliers of the firms in our sample from Factset Revere, similar to Adelino, Ferreira, Giannetti, and Pires (2023). For our sample firms, we observe 14,754 suppliers and 18,932 customers, equivalent to an average of 6.89 suppliers and 4.05 customers per firm.

Supply chain shortages We measure supply chain shortages using data from the Survey of Purchasing Managers, which is the foundation for the construction of the Purchasing Manager Indexes (PMI), compiled by S&P Global for more than forty economies worldwide.[1] Each national PMI dataset is collected from questionnaire responses from senior purchasing executives (or similar) at around 400 companies around the world. To ensure that the survey data are as representative as possible, according to S&P, in each country the panel of companies is selected to accurately represent the true structure of the chosen sector of the economy as determined by official data. PMI data are aggregated at the sector-region level for 37 sectors in Europe, Asia, and the U.S.[2] Participants' survey responses are weighted according to their workforce size. The survey panels, therefore, are assembled to replicate the structure of the sector being monitored.

The questionnaire responses allow the construction of indexes covering different drivers of economic performance at the sector-region level. Our measure of supply chain shortages is suppliers' *Delivery Time*. The suppliers' delivery time index is based on survey participants'

[1] https://www.spglobal.com/marketintelligence/en/mi/products/pmi.html.

[2] The sector coverage varies by geographical areas. We map sectors to SIC codes using the industry code in the British classification system provided by S&P after manually matching the British codes to the U.S. SIC codes. Overall, the 37 sectors are: Basic Materials; Chemicals; Resources; Forestry and Paper Products; Metals and Mining; Consumer Goods; Automobiles and Auto Parts; Beverages and Food; Food; Beverages; Household and Personal Use Products; Consumer Services; Media; Tourism and Recreation; Consumer Cyclicals; Consumer Non-cyclicals; Financials; Banks; Insurance; Other Financials; Real Estate; Healthcare; Healthcare Services; Pharmaceuticals and Biotechnology; Industrials; Industrial Goods; Machinery and Equipment; Construction Materials; Industrial Services; Commercial and Professional Services; General Industrials; Construction and Engineering; Transportation; Technology; Technology Equipment; Software and Services; Telecommunication Services.

responses on whether it is taking the firm's suppliers more or less time to provide inputs on average.[3] The percentage of companies reporting an improvement, deterioration, or no change in delivery times are weighted to derive an index as follows:

$$\begin{aligned} Delivery\ Time = & \%\, percentage\, of\, survey\, panel\, responding\, \text{“}Faster\text{”} \\ & + 0.5 \times \%\, of\, survey\, panel\, responding\, \text{“}Same\text{”} \end{aligned} \tag{1}$$

Thus, readings of the *Delivery Time* index of 50 indicate no change in delivery times relative to the prior month, readings above 50 indicate that delivery times have improved (i.e., become shorter), and readings below 50 indicate that delivery times have deteriorated (i.e., become slower). The index is also seasonally adjusted. For ease of interpretation, in our analyses, we change the sign of the suppliers' delivery times so that an increase in this variable captures a deterioration of supply chain conditions. In addition, while the index is available at a monthly frequency, we consider the average over the previous twelve months for two reasons. First, our firm level data are yearly. Second, even if as we explain below, our inflation data are monthly, we do not expect the effects of supply chain shortages to be immediate.

Since the suppliers' delivery time index is available at the sector-region level, it appears in our analysis as an industry-level variable, capturing the shortages that firms in an industry are facing.

In Figure 1, in red, we plot the time series of the average of our proxy for supply chain disruption across industries and countries. The measure spikes in 2021, at the end of the

[3] https://www.spglobal.com/marketintelligence/en/mi/research-analysis/understanding--pmi-suppliers-delivery-times-a-widely-used-indicator-of-supply-delays-capacity-constraints-and-price-pressures-jul21.html. The precise question wording is: *Are your suppliers' delivery times slower, faster, or unchanged on average than one month ago?*

sample. During the Covid-19 pandemic, not only did an increasing number of companies report supply chain shortages over the previous month, but it also happened for several months in a row, indicating a build-up in bottlenecks.

Maritime Shipments and Port Congestion We obtain Bill of Lading (BoL) data for U.S. maritime imports of products in the Consumer, Energy and Utilities, Financials, Healthcare, Industrials, Materials, Real Estate, Technology, Media and Telecommunications industries from S&P Panjiva. While this data source does not cover all suppliers' shipments, it provides significant coverage of international trade because most international trade flows are seaborn, and any disruptions are likely to trickle down to domestic producers.

A BoL is a legal document used for customer declaration that serves as a record that a shipment has been transported from its origin to its destination. It also details the contract between the shipper and consignee. BoL requires companies to fill out various fields, including shipper/consignee name and address, description of the goods, vessel name, ports of lading (loading) and unlading (unloading), weight, quantity, and container information.

Our dataset covers maritime shipments to the U.S. from 2007 to 2023, though our sample starts in 2010 and ends in 2021 to align with the availability of PMI's Delivery Time for the U.S.

We use the BoL data in two ways.

Bilateral Shipments First, to evaluate the effects of supply chain shortages on trade flows between a supplier and its customers, we merge the shipments to the consignee using the S&P ultimate parent company identifier. We then aggregate shipments from a given shipper to the U.S. consignee at the quarter level. Our proxies capture the extensive margin of shipments – i.e., the number of shipper-consignee pairs that are active within a quarter – and the intensive margin of shipments – i.e., the number of containers, shipments, the number of items, and their volume and weight that a shipper sent to a given consignee during a quarter.

Industry Exposure to Supply Chain Shortages Second, we use information on vessel arrival times to construct an industry-level proxy for exposure to port congestion. The goal is to construct a shift-share instrument for supply chain shortages at the industry level. Utilizing the approach by Flaaen, Haberkorn, Monken, Pierce, Rhodes, and Yi (2022), we transform raw BoL data into a dataset that tracks vessel arrivals to U.S. ports. Then, we calculate the number of days between return arrivals of a given vessel and calculate the monthly average value for a given port. Vessels operate fixed itineraries between ports that serve for freight collection and distribution. In normal times, waiting times at ports are just a few hours. Disruptions related to the Covid-19 pandemic led to extended delays, with waiting times reaching 2-3 days at several major ports, incurring substantial financial losses (Bai, Fernández-Villaverde, Li, and Zanetti, 2024).

To capture elevated delay costs and far-reaching trickle-down consequences for supply chains, we consider a port congested if the average vessel's round-trip arrival time is at least 5 days longer than in the previous month.[4] To give a sense of the magnitude of delays caused by notable events, we report that the average round-trip time to reach the port of Seattle-Tacoma in 2011, following the Great East Japan Earthquake, rose from 93 days before the earthquake to 98 days. In the same period, the time to reach the Oakland port went up from 107 to 114 days. During the Covid-19 crisis, in 2020, the average round-trip voyage to the twin ports of Los Angeles-Long Beach increased from 124 before the crisis to 192, so that Covid-19 qualifies as the most important shock to port activity in our sample.

We then capture industries' different exposures to port disruptions using the fraction of shipments that a 2-digit industry obtains from a given port at the beginning of the sample ($Industry\ Exposure$). We multiply this exposure variable by the time series of port

[4] We choose 5 days as it is the cutoff for the top tercile in the distribution of vessel delays relative to the previous month.

congestion. Formally, for each industry i and month t, we define *Industry Exposure Delays* as

$$Industry\ Exposure\ Delays_{i,t} = 100 \times \sum_j Industry\ Exposure_{i,j} \times (slower\_port_{j,t} + 0.5 \times same\_transit\_time\_port_{j,t}) \tag{2}$$

where *slower_port* is a dummy denoting a port whose average transit time has increased by more than five days vis-a-vis the previous month, and *same_transit_time_port* is a dummy denoting a port whose transit times are within a range of -5 to +5 days relative to the previous month. Since our data contain 52 ports, Equation (2) is the industry-exposure-weighted average of port congestion in a given month. In the regressions, we use the average of the variable in the previous 12 months.

The objective of our industry-level measure of exposure to port disruptions is to capture increases in suppliers' delivery time that are due to operating shocks affecting the suppliers' ability to produce or deliver the input, rather than increases in industry' demand. We provide additional discussion around the validity of this instrument in Section 3.2.

Inflation data We obtain inflation data at the industry-country level from Bloomberg, which in turn reports the series from the relevant statistical authorities. Different countries display different levels of industry aggregation, with the United States having the most granular level of aggregation.[5] Bloomberg does not provide an industry identification code.

[5]For example, in the U.S., the group of non-alcoholic beverages is disaggregated into Juices and Non-alcoholic Drinks – which in turn comprises Carbonated Drinks, Frozen Noncarbonated Juices and Drinks, Nonfrozen noncarbonated Juices and Drinks – Beverage Materials including Coffee and Tea which in turn is comprised of Coffee, Roasted coffee, Instant & Freeze Dried Coffee, Other Beverage Materials Including Tea. In the UK, the group of non-alcoholic beverages contains the two subcategories Coffee, Tea and Cocoa, and Mineral Water, Soft Drinks and Fruit and Vegetable Juices. Finally, in Switzerland, non-alcoholic beverages are in the same category with food: Food and Nonalcoholic Beverages.

Therefore, we conduct a manual reconciliation of the industries in the inflation data set with the industries in the rest of our analysis.

The monthly inflation series consists of the annual change in the monthly consumer price index for the relevant industry.[6] We prefer the seasonally adjusted series whenever they are available.

3 Effects of Supply Chain Shortages across Firms

3.1 First Evidence of Differential Exposure to Supply Chain Shortages

A priori, it is unclear in what direction different firms within an industry will be impacted by supply chain disruptions. The outcome of supply chain shortages on the competitive structure of an industry ultimately depends on which firms can benefit in relative terms. In this section, we investigate this issue.

Using data from Factset Revere, Table 3 provides evidence that firms we classify as superstars have a lower share of domestic suppliers. While suppliers' distance can increase large firms' exposure to shortages, we also find that large firms have more numerous suppliers within a two-digit industry, suggesting that they have several alternative sources for the same input and are, therefore, better diversified. Columns (3) and (4) show that superstar firms are more likely to be associated with customers that we also classify as superstars. Thus, if superstar suppliers are more resilient to shocks, so will be their superstar customers. Overall, the evidence in Table 3 suggests that large firms may suffer less from supply chain disruptions because they have several providers of the same good, and the effect is reinforced by the fact

[6] Our dataset includes Canada, China, Denmark, Eurozone, Hong Kong, India, Israel, Japan, Norway, Singapore, South Korea, Switzerland, United Kingdom, and the United States. For Norway, we use the index of producer prices because no other series is available in Bloomberg.

their suppliers are also large firms. However, this evidence is only suggestive of a differential effect.

To directly assess whether large and small firms are differently exposed to supply chain shortages, we use the shipment data constructed from Panjiva. In particular, we study whether superstar firms obtain relatively larger and more frequent shipments from the same supplier when their industry experiences shortages, which we proxy using the suppliers' delivery time index. We control non-parametrically for shocks affecting the supplier by including interactions of time and supplier fixed effects. We also absorb industry conditions by including interactions of industry and time fixed effects.

Table 4 presents the results using ordinary least squares (Panel A) and a Poisson model (Panel B).[7] The estimates in column (1) of Panel A show that, relative to their smaller competitors, superstar firms are more likely to receive a shipment in quarters with longer suppliers' delivery time. From columns (2) through (6) of Panel A, we observe that the number of containers, the number of shipments, their weight, their volume, and their quantity increase for superstar firms relative to other companies when suppliers' delivery times are longer. The estimates are not only statistically but also economically significant. For instance, a one-standard-deviation increase in *Delivery Time* is associated with 0.981 more containers and 16.5 more tons shipped to superstar customers, which corresponds to 21% and 15% of the average values, respectively. The inference is similar in Panel B.

Overall, Table 4 suggests that suppliers discriminate between customers favoring superstar firms when negative shocks prevent them from satisfying all orders. In these situations, superstar firms may also benefit from demand shocks because their reputation makes them more reliable suppliers when shortages occur. Irrespective of whether it is a supply or demand shock, superstar firms benefit from input rationing due to supply chain shortages.

[7] Our results are unchanged if we take the logarithm of the dependent variable to address the fact that the distribution may be skewed. The estimates based on the Poisson model help assuage this concern while being exempt from the biases highlighted by Cohn, Liu, and Wardlaw (2022).

Thus, Table 4 is consistent with the idea that superstar firms are in a better condition to produce when supply chain shortages occur.

3.2 Identification of Supply Shocks

A cost shock due to supply chain shortages and a demand reallocation shock triggered by the expectation of asymmetric disruptions in supply chains have equivalent equilibrium implications, as we will show in our theoretical framework below. Thus, we view our empirical evidence as consistent with both interpretations. A separate concern, however, is that a positive demand shock only directed to the superstar firms may ultimately induce congestion of supply chains, raising an issue of reverse causality that would cloud the interpretation of our results. For example, if positive consumer sentiment translates into more demand for the products of the largest firms in an industry, which consequently order more inputs from their suppliers, increasing their delivery times, our proxy for supply chain shortages may be contaminated by a demand shock.

To identify variation in delivery times that is unlikely to arise from demand shocks experienced by superstar firms, we use the *Industry Exposure Delays* shift-share instrument whose construction is described in Section 2. The instrument captures industry exposure to port congestion. The *shift* component of our instrument is the congestion of global ports, which is unlikely to be determined by demand affecting specific firms. Indeed, the maximum fraction of port shipments attributable to a superstar consignee is 2.6% on average across years and ports. This number suggests that the traffic imputable to a unique large firm is too small to generate port congestion.

The *share* component is pre-determined, being the industry exposure to the ports at the beginning of the sample. Since we aim to capture differences between firms in an industry and always include interactions of industry and time fixed effects, the share component of our instrument can safely be considered exogenous.

Table 5 presents the 2SLS estimates. For this analysis, we focus on the Covid-19 period (2019-2021), when the frictions arising from port congestion are stronger.[8] Column (1) presents the first stage. Since we want to instrument the variable *Delivery Time*, which appears in the second stage in an interaction with superstar, we interact *Industry Exposure Delays* with the superstar indicator to obtain the instrument[9]. The instrument has a positive and significant effect, as expected, and the F-test of excluded instruments shows that we do not incur a weak instrument problem. The second stage estimates fully support our earlier findings, suggesting that when suppliers have to fill their past orders, they favor superstar firms.

The 2SLS estimates in Table 5 appear significantly larger than the corresponding OLS estimates in Table 4, Panel A.[10] The OLS estimates could be downward biased by measurement error in the delivery time variable, which, as is evident from Figure 1, exhibits much less variability than our instrumental variable. However, it is important to note that by construction, the *Industry Exposure Delays* instrument captures the most severe episodes of supply chain shortages affecting an industry. Hence, the instrumental variable estimates capture a local average treatment effect that is naturally larger.

4 Theoretical Framework

In what follows, we develop a simple theoretical framework to study the implications regarding firm-level and industry-level outcomes of shocks that asymmetrically affect the firms within an industry. The premise of this analysis is that supply chain disruptions can harm large firms less than their smaller competitors. Consistent with the empirical

[8] In this analysis as well as in later analyses, we let the Covid-19 sample start in 2019 to have a year before the start of the pandemic that we can use as a benchmark.

[9] The direct effect of *Industry Exposure Delays* is absorbed by the interaction of industry and time fixed effects

[10] Similar patterns in the estimated coefficients are found in the later analysis also using the Industry Exposure Delays instrument.

evidence in Section 3, several arguments suggest that supply chain shortages may be less harmful to superstar firms. First, as suggested by theory and empirical evidence (Klein, Crawford, and Alchian, 1978, Williamson, 1979, Chipty and Snyder, 1999, Inderst and Wey, 2007, Draganska, Klapper, and Villas-Boas, 2010), we recognize that the larger firms within an industry tend to have more bargaining power vis-à-vis their suppliers, who consequently grant them preferential treatment in case of production backlogs. Second, large firms are also more likely to have the scale to internalize some upstream activities, or have suppliers that are themselves superstars, as shown in Table 3, and are, therefore, less negatively affected by supply chain shocks. These mechanisms suggest that superstar companies are more likely to be able to operate close to the optimal mix of production than their smaller rivals following supply chain shortages, and, as a result, they experience lower increases in production costs.

We consider an industry populated by n firms producing perfect substitute products. The firms are oligopolists following Cournot competition. Thus, each firm maximizes its profit considering the price impact of its output choice, q_i. The firms face constant return to scale with marginal cost c_i. To capture supply chain shortages and their asymmetric effects, we let

$$c_i = \delta_i \sigma \tag{3}$$

where $\delta_i > 0$ and $\sum_{j=1}^{n} \delta_j = 1$, without loss of generality. The parameter σ captures aggregate factors affecting delivery times in an industry and δ_j firm j's exposure to these factors. Under our parametrization, if $\delta_j = 1/n$ for all j, then all firms are equally exposed to supply chain shocks; to capture that superstar firms are less exposed to aggregate shocks originating from supply chains and also larger and more efficient, we assume that $\delta_j < 1/n$ for superstar firms. Thus, superstar firms always receive inputs at lower cost. Importantly, an increase in the parameter σ, capturing supply chain shortages, leads to increased dispersion in the costs of the firms within the industry. We aim to describe how industry structure and prices change when σ increases.

For simplicity, we assume that the aggregate demand for the product is linear

$$p(Q) = b - Q, \tag{4}$$

where $Q = \sum_{j=1}^{n} q_j$.[11]

Solving firm i's profit maximization and for the industry equilibrium, we obtain firms' market shares. All proofs are presented in the Appendix. It follows readily from our assumptions that superstar firms, having lower costs, have higher market shares, profits, and markups. Importantly, as established in Proposition 1 below, their advantage increases when supply chain shortages (σ) increase.

Proposition 1. ***Supply Shortages and Firms' Market Shares*** *In equilibrium, firm i's market share and markup increase when supply chain shortages increase marginal costs for all firms if and only if* $\delta_i < 1/n$.

Proposition 1 provides the testable implications for the first part of our empirical analysis. Firms that are less exposed to supply chain shortages because they have a lower δ_i gain a competitive advantage when σ increases because the difference in costs between them and their competitors is larger. In our empirical analysis, we use firm size and firms' superstar status as an inverse proxy for δ_i. Thus, supply chain shortages accentuate small firms' cost disadvantage. Consequently, a larger fraction of the product will be provided by the largest firms, which facing less competitive pressure benefit from an increase in their market power. Specifically, the higher cost of the smaller competitors implies that the equilibrium price will increase more than the cost of superstar firms. This allows superstar firms not only to expand their market share, but also to increase their profitability and markups.

Besides testing the firm-level implications, we also evaluate the industry-level conse-

[11] To obtain positive aggregate production in equilibrium, we assume that $nb - c > 0$ and, to have a positive equilibrium output for each firm, we let $b + c - (1 + n) c_i > 0$.

quences of supply chain shortages. Supply chain shortages increase the difference in production costs between superstar firms and their competitors. We therefore expect supply chain shortages to have a larger impact on the structure of industries in which firms differ most in their exposure to the shortages, δ_i. By construction, these are industries with ex ante higher concentration, which we capture using the Herfindahl–Hirschman Index ($HHI = \sum_{j=1}^{n} s_j^2$). The following proposition proves that an increase in supply chain shortages leads to higher concentration and lower output in industries with ex-ante higher HHI.

Proposition 2. *Supply chain shortages, captured by an increase in σ, lead to an increase in the dispersion of market shares across firms and to an increase in the industry's HHI, which is more pronounced for industries with ex-ante higher HHI. The decrease in output is also more pronounced in ex ante more concentrated industries.*

This result allows us to derive a relation between supply chain shortages and markup increases. In a Cournot equilibrium, a relation between the average industry markup and HHI can be easily derived from firms' first-order conditions. Firm i's first order condition is: $P(Q) + \frac{\partial p}{\partial Q} q_i - c_i = 0$, which can be rewritten as $\frac{p-c_i}{p} = -\frac{\partial p}{\partial Q}\frac{Q}{p}\frac{q_i}{Q} = s_i/|\epsilon|$, where ϵ is the elasticity of demand and s_i the market share of firm i. To obtain the relationship between average industry markup and HHI, we take the market-share-weighted average of the firms' first order conditions:

$$\sum_{j=1}^{n} s_j \frac{p-c_j}{p} = \frac{1}{|\varepsilon|} \sum_{j=1}^{n} s_j^2 = \frac{1}{|\varepsilon|} HHI. \tag{5}$$

Equation 5 implies that an increase in HHI, due, for instance, to higher supply chain shortages, will be associated with higher industry markups, which in turn imply a more pronounced increase in price level for a given cost shock. Based on Proposition 2, we thus expect a higher increase in prices when supply chain shortages occur in industries with ex-ante higher HHI. Because aggregate markups increase and a larger share of the product is supplied by high markup firms, industry profits also increase more in ex ante more concentrated industries.[12]

Proposition 2 motivates the second part of our empirical analysis. An implication of the asymmetric effects of supply chain shortages across firms in an industry is that we expect heterogeneous price increases depending on the industries' ex-ante competitive structure. Not only do we test whether supply chain shortages are associated with a more pronounced increase in concentration in industries starting from higher levels of concentration, but we also expect that the negative effect of supply chain disruptions on aggregate sales and the positive effect on inflation are stronger in more concentrated industries.

So far, we have discussed the effects of supply chain shortages arising from a heterogeneous cost shock in a framework with a homogenous product. However, supply chain shortages could also coincide with an increase in demand for superstar firms, which, being favored by their suppliers, are also more reliable suppliers of the product when shortages occur. The equilibrium implications of this alternative scenario are observationally equivalent to those arising from an asymmetric cost shock. To see this, we generalize our simple framework to allow for heterogeneous demand shocks. Specifically, firm i faces the following demand $p_i(Q) = b_i - q_i - k \sum_{j \neq i \in [1,n]} q_j$, where $k < 1$ captures the extent of substitutability between firm i's product and the products of the other firms. Since profits can be written as $(b_i - q_i - k \sum_{j=1}^{n} q_j - c_i)q_i$, it is evident that a relative increase in b_i is equivalent to a smaller cost shock for firm i. We prove this claim in Appendix Section C where we derive the solution of the model with heterogeneous products.

[12] It is pedagogical to consider how the equilibrium would change without asymmetric cost shocks, that is, if $\delta_j = 1/n$ for all j. In this case, all firms would experience the same cost shock. An increase in σ would decrease the markup for all firms in the industry. Furthermore, since the relative competitiveness of firms would be unchanged, the industry structure would not vary.

5 Supply Chain Shortages and Firm-Level Outcomes

5.1 Main Findings

Having shown in Section 3 that supply chain shortages have heterogeneous effects on firms based on their size, next we study whether they affect firms' outcomes, as predicted by the theoretical framework of Section 4. For this analysis, we do not need to use maritime shipments data, which is available to us only for U.S. firms. Thus, we start from considering an international sample.

Motivated by Proposition 1, we first focus on firms' market shares and profitability, which are predicted to improve for superstar firms. We compute market share as the fraction of a firm's sales over the total sales of firms in the same two-digit SIC-code industry (labeled *% of industry sales*). Similar to De Loecker, Eeckhout, and Unger (2020), we measure profitability with the return on assets (*ROA*), defined as sales minus cost of goods sold (COGS), selling, general, and administrative expenses (SG&A), and the opportunity cost of capital, obtained by multiplying property, plant, and equipment by the real interest rate, computed as in De Loecker, Eeckhout, and Unger (2020).

Figure 2 illustrates our main finding plotting the market shares of superstar firms and their competitors in periods of high and low supply chain shortages. It appears that superstar firms gain market share relative to their competitors in periods with supply chain bottlenecks.

Table 6 considers the continuous version of the supply chain shortages proxy and reports the estimates from regressing the outcome variables on the interaction of *Delivery time* and an indicator for superstar firms, *Star*. We include industry-by-country-by-year fixed effects to capture industry- and country-specific shocks and cluster standard errors at the firm level.

Table 6 considers the entire sample period (2010-2021) as well as the period around the Covid-19 pandemic. In columns (1) and (2), we observe that superstar firms experience an increase in market share following a deterioration of the supply chain conditions. Moreover, in columns (3) and (4), we observe that superstar firms' profitability increases.[13] The effect is robust whether we consider the whole sample period or we focus on the period around the Covid-19 pandemic. Importantly, the estimates are not only statistically, but also economically significant. For example, the coefficient in column (1) implies that a one-standard-deviation increase in *Delivery Time* increases the market share of star firms by 3.7% of a standard deviation, which is equivalent to around 11% of the average market share. This figure goes up to 59% of the average value when we consider ROA in column (3).[14] These results suggest that larger firms are more resilient when bottlenecks emerge and consequently better able to satisfy market demand. We emphasize that supply chain disruptions appear different from shocks that increase competition in an industry, such as those explored by Ayyagari, Demirguc-Kunt, and Maksimovic (2023), which have been shown to affect all firms in an industry to the same extent.

For robustness, in columns (5)-(8) of Table 6, we take as dependent variables the first differences of the outcome variables of interest. This allows us to control for the fact that not only star firms have, by definition, higher market shares and are more profitable, but also that they may be on a trajectory of acquiring larger market shares while enhancing their overall performance. The estimates are consistent with our prior findings and suggest that, on average, superstar firms increase their market shares and improve their profitability in comparison to other firms facing backlogs. Also for these specifications, the effects appear stronger in the Covid-19 subsample.

Importantly, the changes in market share we highlight appear to be permanent. In Figure 3, we plot the dynamics of the effects of an increase in delivery times for superstar

[13]The direct effect of our proxy for supply chain shortages variable is absorbed by the industry-by-country-by-year fixed effects.

[14]As shown in Table 2, the average of the variable % industry sales is 0.259 and the standard deviation 0.761. Thus, 3.7% of a standard deviation corresponds to 0.028(=0.037×0.916). Similar calculations apply to the coefficient for ROA.

firms using local projections. We plot the estimated effect of a one-standard-deviation change in delivery times on the change in market share of a superstar firm over time (Panel A). It appears that supply chain shortages translate in an increase in market share for superstar firms during the following year, while subsequent changes are not statistically different from zero, indicating the changes in market structure are persistent. We find, however, that a similar shock is followed by only a temporary increase in superstar firms' profitability (Panel B), suggesting that when supply chain shortages subside, potential entrants erode superstar firms' market power, even if they do not enter the market and do not impact the superstars' newly acquired market share.

5.2 Exploiting Variation in Port Congestion

To focus on shortages arising from supply-side frictions, we exploit *Industry Exposure Delays* as an instrument. Since we can construct the instrument only for U.S. ports, as in the tests of Table 4, we focus on U.S. firms. Table 7 shows the 2SLS estimates in the full sample as well as during the Covid period. Table A1 in the Internet Appendix shows the reduced form estimates.

The regression coefficients fully confirm our previous findings and support that supply chain relationships affect industry structure when shortages occur.

5.3 Markups and Costs

The evidence that market shares and profitability increase for large firms relative to the smaller ones suggests that the former are taking advantage of an improvement in their competitive position. However, firms' profitability can rise if large firms can produce more than other firms and increase their sales when backlogs are high. Therefore, an increase in dollar profits is not necessarily associated with an increase in markups if costs increase more than prices (Syverson, 2019). Thus, higher market share and profits may not necessarily imply more market power because they may arise as a result of an increase in units sold with decreasing profit margins.

To evaluate whether superstar firms' market power increases due to supply chain shortages, we investigate whether the markups of superstar firms increase relative to other firms in the same industry and country. In the absence of information on product prices and marginal costs, we follow existing literature and define markups as sales divided by variable costs, which we construct as operating expenses minus R&D expenses and 30% of Selling, General, and Administrative Expenses (SG&A) expenses, following Ayyagari, Demirguc-Kunt, and Maksimovic (2023).

The estimates in Table 8 show that consistent with previous literature, superstar firms always have higher markups. More importantly, superstar firms' markups increase relative to other firms in the same industry when supply chain shortages occur. These results are not only statistically significant, but their economic magnitude is sizable. For example, in column (1), a one-standard-deviation increase in *Delivery Time* leads to 5.8% of a standard deviation increase in the markups for star firms, which corresponds to 30% of the average logarithmic markups in the sample.[15]

Importantly, all our specifications control for cost shocks, which superstar firms may pass through on prices to a larger extent thanks to their market power (Bräuning, Fillat, and Joaquim, 2022, Konczal and Lusiani, 2022), indicating that the channel we highlight is distinct. To measure firm level changes in costs, we use the contemporaneous percentage change in the cost of goods sold. We include this proxy for cost shock in the regression and interact it with the superstar firm indicator. We observe mixed evidence on whether superstar firms' pass-through level is larger than for other firms, as this seems to be the case when we consider the markup in levels as the dependent variable, but we obtain the opposite

[15] As shown in Table 2, the average logarithmic markups is 0.089 and the standard deviation 0.458. Thus, 5.8% of a standard deviation corresponds to 0.027(=0.058×0.426).

sign when we consider the change in markup.

In Table A2, we show that our results are qualitatively invariant if we alter the definition of markup using different definitions of costs in the denominator. Specifically following De Loecker, Eeckhout, and Unger (2020), we add SG&A to the cost of goods sold and an estimate of the user cost of capital. We also consider an alternative definition that only considers the costs of goods sold at the denominator.

Overall, it appears that supply chain shortages increase superstar firms' pricing power. We also test that the mechanism that we propose, based on a differential effect of the supply chain bottlenecks on firms within an industry, is at play. In Table 9, the dependent variable is a firm's change in the cost of goods sold. We test whether, in periods of more pronounced supply chain shortages, superstar firms experience lower increases in costs than other firms within an industry. The evidence supports this conjecture. The coefficient of -0.022 in column (1) suggests that when *Delivery Time* increases by one standard deviation, star firms experience a decrease in costs of goods sold of 2.2% of a standard deviation relative to other firms. This is equivalent to a drop of around 9.1bps, or 10% of the average value.[16]

It is also interesting to study the relative importance of price increases and cost decreases in the observed increase in large firms' markups. Superstar firms' (relative) reduction in costs of 0.91% associated with supply chain shortages would imply a markup of 1.258 = Sales/New Costs = Sales/(Old Costs*(1+Delta Costs))=1.247/(1-0.0091).[17] That is, if the markup changed only because superstar firms have lower costs relative to their competitors (and there were no changes in prices), the new markup of superstar firms after the shock should be 1.258, equivalent to an increase of 0.011 = 1.258-1.247. However, in column (3) of Table 8, a one-standard-deviation increase in delivery time is associated with an increase in superstar firms' markups by 6.9% of a standard deviation, or 0.0228 (the sample standard

[16] As shown in Table 2, the average change in COGS is 0.089, and the standard deviation is 0.415. Thus, 2.2% of a standard deviation corresponds to 0.0091 (=0.022×0.415).

[17] 1.247 is the markup (=Sales/Old Costs) for star firms in 2019 (before the shock).

deviation of markup is 0.331). The reduced costs can explain only 48% (0.011/0.0228) of superstar firms' markup increase, indicating that the remaining 52% of the markup increase can be imputed to superstar firms exploiting the relative increase in their competitors' costs to increase prices.

5.4 Evidence from Superstars' Stock Market Performance

The period after the Covid-19 pandemic has been characterized by strong stock market performance for large firms. The mechanism we study in this paper, implying higher profitability and market share for large firms, could translate into higher stock returns for superstar firms.

Based on the international sample, Table 10 shows that superstar firms' monthly raw returns and abnormal returns relative the MSCI index are systematically higher when their industry experiences delivery delays. The result holds both in the whole sample and when we focus on the period around the Covid-19 pandemic.

Not only are our results statistically significant, but the economic magnitude is also sizeable. In the most restrictive specification of column (4), we find that, in the period around the Covid-19 pandemic, a one-standard-deviation increase in delivery times is associated with 35 bps higher monthly returns for superstar firms. The monthly outperformance of superstar firms relative to other companies in the Covid-19 sample was about 33 bps on average. The average value of the delivery time variable is 0.33 units of standard deviation above the mean in this sample. Thus, based on our estimates, the effect of supply chain shortages can explain about a third of the outperformance of superstar firms during this period.

5.5 Alternative Mechanisms

5.5.1 Placebo: Other Cost Shocks

As our simple framework makes clear, we think of supply chain shortages as cost shocks that arise from limited access to inputs, where the rationing is more severe for smaller firms. To construct a placebo, we consider energy price shocks that are likely to affect all firms in an industry similarly because, for a given price, firms should be able to satisfy their demand, irrespective of their size. Thus, we do not expect energy price shocks to lead to increases of market share and profitability for superstar firms.

We study this conjecture in Table A3 of the Internet Appendix. Besides including the interaction of the energy price change with the superstar firm dummy, we also allow for different industries to exhibit different dependence on energy by including an interaction of the superstar dummy with the average emission level in an industry.[18] When energy shocks occur, superstar firms and superstar firms in more energy-intensive industries do not appear to experience an increase in market share and profitability, as is consistent with the fact that energy shocks translate into price increases for all firms but no quantity rationing.

5.5.2 Financial Constraints

Markups have been shown to vary over the business cycle: During recessions, financial frictions can constrain firm scale leading firms to optimally increase prices (Chevalier and Scharfstein, 1996). Such a mechanism would imply higher markups for the more constrained small firms that are less likely to be able to produce at capacity, and its implications contrast with the evidence we present. In addition, supply chain shortages do not necessarily coincide with periods in which financial frictions are more pronounced. For instance, during the Covid-19 pandemic, government interventions significantly decreased firms' cost of capital.

[18] *Industry Emissions* is the average GHG scope 1 and scope 2 emission intensity from Trucost.

Even though we view our mechanism as distinct from financial constraints and, more generally, financial resilience, we evaluate to what extent financial frictions can contribute to explain our findings. We use the average interest rate firms pay on their outstanding liabilities as a proxy for the cost of external finance. Specifically, we consider as financially constrained the firms for which average interest rate is in the top tercile of the country during the year. In Table A4 of the Internet Appendix, we interact this dummy, capturing the most financially constrained firms at $t-1$, with *Delivery Time* and run a horse race. While we find only weak evidence that financial constraints tend to decrease firms' sales and profitability in periods with high supply chain shortages, the coefficient on the interaction between *Star* and *Delivery Time* remains positive and significant suggesting that the extent to which firms are exposed to financial frictions does not drive our findings.

Estimates continue to be equally supportive of our mechanism in columns (5) to (8), where we consider as more financially flexible firms that are in the top tercile for cash-holdings relative to total assets within their country.

5.5.3 Operational Resilience

Next, we consider the possibility that some firms may have been better able to withstand supply chain shocks because they had invested in operational resilience.

Table A5 of the Internet Appendix explores whether the better performance of superstar firms depends on the fact that superstar firms are in a better position to face supply chain shortages thanks to larger inventories. We thus interact our proxy for supply chain shortages with the ratio of a firm's inventory to sales during the previous year. We do not find much evidence that larger inventories help firms acquire market shares and preserve profits when supply chain shortages occur. More importantly, we continue to find that superstar firms acquire market shares and improve their profitability relative to firms experiencing similar supply chain shocks.

Overall, these tests confirm our interpretation of the empirical evidence that firms with dominant positions can take advantage of supply chain shortages to further enhance their market power.

6 Industry Level Outcomes and Inflation

6.1 Industry concentration and output

Because large firms tend to enhance their competitive position during periods of supply chain shortages, our theoretical framework implies that industries that are characterized by the presence of large companies should become even more concentrated when supply chain disruptions occur. As competition decreases, aggregate output in these industries should also decrease.

In what follows, our main proxy for concentration is an industry's Herfindahl-Hirschman index (HHI), which is the sum of firms' squared market shares within the country, computed using sales. This measure has the advantage to be directly related to an industry level of markups within a Cournot model (see Equation (5)).

While concentration can be associated with more or less market power (Syverson, 2019), we aim to capture the presence of large companies that may not suffer as much as their smaller competitors and potential entrants from supply chain shortages, and may consequently experience an increase in their market power. In principle, the HHI could be high in industries with very few equally large firms. While we would not expect supply chain shortages to have a different effect on the costs of firms with similar size, our data include only listed companies. Market power can increase for the largest companies not only because their smaller listed competitors have a harder time securing the necessary inputs, but also because unlisted companies that are not included in our data and potential entrants are deterred by the input shortages. Thus, the HHI is a valid candidate to capture the effects of supply chain shortages that we theorize.

To make sure that the ex ante HHI indeed captures the mechanism behind our theoretical framework, we test whether an industry's HHI increases following years in which the industry experienced an increase in the suppliers' delivery time and whether the effect is driven by industries that were ex ante more concentrated, as predicted by Proposition 2 in our theoretical framework. Table 11 presents the results. With different sets of fixed effects, we find that, indeed, an increase in delivery times leads to higher HHI for industries that started the year with higher levels of HHI, consistent with Proposition 2. We conclude that HHI adequately captures the effects of concentration that are described in our theoretical framework.

Our theoretical framework also implies that an increase in concentration should be associated with lower industry output. Put differently, supply chain shortages causing a decrease in competition should lead to a negative supply shock. Table 12 thus tests whether supply chain shortages translate into a drop in output. Consistent with the model predictions, we find that supply chain shortages are associated with larger drops in aggregate sales in industries that are ex ante more concentrated.

Not only does this result support our theoretical framework, but it also helps to rule out the possibility that the increases in industry concentration and superstar firms' market shares are simply driven by large firms' better ability to satisfy positive demand shocks associated with supply chain shortages. If this were the case, we should observe that aggregate sales increase more in industries that are ex ante more concentrated – i.e., those in which there are more large firms – when supply chain shortages occur. Instead, the fact that aggregate sales experience a relative decrease in industries that are ex ante more concentrated when supply chain shortages occur is consistent with a decrease in output associated with an increase in superstar firms' market power.

6.2 Industry-level Inflation

Since highly concentrated industries become even more concentrated when supply chain shortages occur, we expect prices and, consequently, inflation to increase more in these industries. To test this conjecture, we regress industry-level annual price changes (CPI) at the monthly frequency on the industry HHI interacted with our main measure of supply chain shortages. For this analysis, industries are defined at the country level as we conjecture that local companies have local price-setting power and consequently determine country-level inflation.

We run the following regression model for CPI in industry i, country c and month t:

$$CPI_{i,c,t} = \alpha_{i,c,t} + \beta_1 Delivery\ Time_{i,c,t}^{t-1,t-12} + \beta_2 Delivery\ Time_{i,c,t}^{t-1,t-12} \times Concentration_{i,c} + \varepsilon_{i,c,t} \tag{6}$$

where, $\alpha_{i,c,t}$ represents our different combinations of fixed effects, namely, industry-country-year and year-month. $Delivery\ Time_{i,c,t}^{t-1,t-12}$ is measured in the 12-month interval $[t-1, t-12]$ for industry i in country c. $Concentration_{i,c}$ is either the HHI or one of the alternative proxies for concentration that we introduce below, all defined at the beginning of the sample for industry i in country c to limit reverse causality problems. Standard errors are clustered at the year-month level and adjusted for eleven lags of autocorrelation.

Our hypothesis implies that for given input shortages, inflation should be higher in ex ante more concentrated industries because there are more large firms that are poised to benefit disproportionately from input shortages. Since we control for the direct effect of supply chain shortages on industry inflation, our tests do not merely test for an increase in prices after supply chain disruptions, which can result from the pass-through effect even in a perfectly competitive market. Rather, holding constant the extent of supply chain shortages, we investigate whether the price increases are stronger in industries and countries in which large firms are more likely to experience an increase in market power at the expenses of smaller firms following supply chain disruptions.

Panel A of Table 13 presents the estimates. The coefficient on the variable *Delivery Time* is positive and significant both for the whole sample and for the Covid-19 period, suggesting that this variable can indeed capture increases in input costs associated with shortages. More importantly, consistent with our conjecture, we find that more concentrated industries experience more significant price increases at times of supply chain disruptions. The effect appears particularly large during the Covid-19 period.

We also consider whether our findings may indicate that cost shocks are transferred on prices to a larger extent in high concentration industries. While such an explanation would be inconsistent with the firm level evidence (Table 8), we still take into account the possibility that differences in pass-through may help explaining differences in inflation. In columns (3) and (4) of Table 13, we measure industry level cost shocks summing the cost of goods sold for all firms in an industry during a year and computing the year on year percentage change. We observe that industries with higher increases in costs experience higher inflation. While the pass-through of cost increases appears to be higher in more concentrated industries when we consider the whole sample, in the Covid-19 subsample, we do not observe that the increase in costs translates in higher inflation in more concentrated industries. In contrast, our finding that supply chain shortages translate into higher inflationary pressure in industries with higher concentration is unchanged across specifications.

Panel B of Table 13 considers alternative proxies for industry ex ante concentration. In column (1) and (2), the estimates appear qualitatively and quantitatively unchanged if we measure concentration using the market share of the top four firms in an industry. Also, if one abstracts from potential entrants, our conjecture hinges on the existence of an unequal distribution of firm size, so that the larger firms can subtract market share from smaller firms when the input shortages occur. In the rest of Panel B of Table 13, we capture this possibility considering the presence of superstar firms in a country and industry. Specifically, in columns (3) and (4), we consider the superstar firms' percentage of sales in the industry and country; and in columns (5) and (6), we use a dummy variable for the presence of a superstar in the country-industry pair, both measured at $t-1$ as in our firm level analysis.[19] Consistent with our earlier findings we observe higher inflation in industries and countries with more pronounced presence of superstar firms.

Panel C of Table 13 provides a geographic breakdown of the effect identified in the prior two tables. In particular, we note that the interaction of *Delivery Time* and the proxy for the likelihood that large firms increase their market power is by and large positive and significant in the U.S., and Europe. The economic magnitude of the estimates is not only statistically, but also economically significant. For instance, the coefficient of 1.148 in column (2) of Panel C of Table 13 implies that in the U.S. during the Covid-19 pandemic, the CPI increased by 1.148 percentage points in industries with a one-standard-deviation-above-the-mean delivery time and a one-standard-deviation-above-the-mean HHI.

6.3 Contribution to Aggregate Inflation

The last analysis also allows us to make a statement about the impact of the new mechanism highlighted in this paper on aggregate inflation. To this purpose, we assume that the slope β_2 on the interaction between delivery time and concentration in Equation (7) captures the effect on industry-level inflation of increased market power of superstar firms following supply chain shortages. Then, to obtain the impact on aggregate inflation, we take the sales-weighted average of this effect across industries.

[19]We note that superstars are defined globally at the industry-year level. So, in a given country-industry-year there is not necessarily a superstar firm.

In more detail, we estimate the impact on aggregate inflation as

$$Aggregate\ Effect = \beta_2 \sum_i \left(Weight_i \times HHI_i \times Delivery\ Time_i \right), \tag{7}$$

where we use a value of 0.000079 for β_2 coming from a specification resembling the one in column (2) of Table 13 except for the use of unstandardized variables. The weight of each industry i is the fraction of sales of industry i in 2020. HHI_i is the beginning of sample concentration index for industry i, and $Delivery\ Time_i$ is the average Delivery Time for industry i in 2021.

Using this approach, we estimate an aggregate effect of 1.02%, when we use the average value of *Delivery Time* in 2021, and 1.66%, when we use the value of delivery times in December 2021. Given that the realized CPI inflation in December 2021 in the U.S. sample is 7.10%, the proposed mechanism can explain between 14.4% and 23.4% of the realized inflation in the U.S. in 2021.

Overall, the evidence points to a shift in market share towards superstar firms following supply chain shortages, which led to an increase in the market power of the largest firms. Thus, industries characterized by the presence of superstar firms experienced a decrease in aggregate sales and more significant price spikes. This finding is consistent with the evidence that the pandemic-era inflation was initiated by developments that directly raised prices rather than wages, following supply chain shortages (see, e.g., Bernanke and Blanchard, 2023).

7 Conclusion

We propose a new mechanism through which supply chain shortages increase market power and lead to price hikes. In particular, we conjecture that large firms' competitive position may improve following supply chain shortages because they are better equipped to withstand the disruptions.

Consistent with this conjecture, we show that large firms increase their market shares and experience higher profit margins and markups when supply chain shortages occur. Moreover, we find that more concentrated industries experience larger drops in aggregate sales and higher inflation following supply chain backlogs.

Our results have implications for the transmission of monetary policy. When the mechanism that we study in this paper is at work, monetary policy contractions can become inflationary because small firms are likely to experience stronger financial constraints than large firms, as policy rates rise (Gertler and Gilchrist, 1994). Financial frictions associated with monetary policy contractions may thus increase superstar firms' competitive advantage even further and reduce competition. While interest rate hikes may be ineffective or even counterproductive, the relaxation of supply chain shortages is expected to increase competition, thus leading to lower markups and inflation.

References

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, 2012, The Network Origins of Aggregate Fluctuations, Econometrica 80, 1977–2016.

Acharya, Viral V, Matteo Crosignani, Tim Eisert, and Christian Eufinger, 2023a, How do supply shocks to inflation generalize? The role of market power and household expectations, Working Paper.

——— , 2023b, Zombie Credit and (Dis-) Inflation: Evidence from Europe, The Journal of Finance [Forthcoming].

Adelino, Manuel, Miguel A Ferreira, Mariassunta Giannetti, and Pedro Pires, 2023, Trade Credit and the Transmission of Unconventional Monetary Policy, The Review of Financial Studies 36, 775–813.

Antoun de Almeida, Luiza, 2015, Firms' balance sheets and sectoral inflation in the euro area during the financial crisis, Economics Letters 135, 31–33.

Antràs, Pol, and Davin Chor, 2022, Global value chains, in Handbook of International Economicsvol. 5 . pp. 297–376 (Elsevier B.V.).

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen, 2020, The Fall of the Labor Share and the Rise of Superstar Firms, The Quarterly Journal of Economics 135, 645–709.

Ayyagari, Meghana, Asli Demirguc-Kunt, and Vojislav Maksimovic, 2023, The Rise of Star Firms: Intangible Capital and Competition, Review of Financial Studies [forthcoming].

Bai, Xiwen, Jesús Fernández-Villaverde, Yiliang Li, and Francesco Zanetti, 2024, The causal effects of global supply chain disruptions on macroeconomic outcomes: evidence and theory, CESifo Working Paper.

Barrot, Jean Noel, and Julien Sauvagnat, 2016, Input Specificity and the Propagation of Shocks in Production Networks, The Quarterly Journal of Economics pp. 1543–1592.

Barth, Marvin J., and Valerie A. Ramey, 2001, The cost channel of monetary transmission - Revisited, NBER Macroeconomics Annual 16, 199–240.

Bernanke, Ben, and Olivier Blanchard, 2023, What caused the us pandemic-era inflation?, Peterson Institute for International Economics Working Paper 23–4.

———, 2024, An analysis of pandemic-era inflation in 11 economies, Peterson Institute for International Economics Working Paper 24–11.

Bräuning, Falk, José L. Fillat, and Gustavo Joaquim, 2022, Cost-Price Relationships in a Concentrated Economy, Working Paper.

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

Chevalier, By Judith A, and David S. Scharfstein, 1996, Capital-Market Imperfections and Countercyclical Markups: Theory and Evidence, The American Economic Review 86, 703–725.

Chipty, Tasneem, and Christopher M. Snyder, 1999, The Role of Firm Size in Bilateral Bargaining: A Study of the Cable Television Industry, Review of Economics and Statistics 81, 326–340.

Cohn, Jonathan B, Zack Liu, and Malcolm I Wardlaw, 2022, Count (and count-like) data in finance, Journal of Financial Economics 146, 529–551.

De Loecker, Jan, and Jan Eeckhout, 2018, Global Market Power, Working Paper.

———, and Gabriel Unger, 2020, The Rise of Market Power and the Macroeconomic Implications, The Quarterly Journal of Economics 135, 561–644.

Di Giovanni, Julian di, Ṣebnem Kalemli-Özcan, Alvaro Silva, and Muhammed Yildirim, 2023, Pandemic-Era Inflation Drivers and Global Spillovers, Working Paper.

Draganska, Michaela, Daniel Klapper, and Sofia B. Villas-Boas, 2010, A Larger Slice or a Larger Pie? An Empirical Investigation of Bargaining Power in the Distribution Channel, Marketing Science 29, 57–74.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2023, Credit Crunches and the Great Stagflation, Working Paper.

Eeckhout, Jan, and Laura Veldkamp, 2022, Data and market power, .

Ersahin, Nuri, Mariassunta Giannetti, and Ruidi Huang, 2024, Trade Credit and the Stability of Supply Chains, Journal of International Economics.

Flaaen, Aaron, Flora Haberkorn, Anderson Monken, Justin Pierce, Rosemary Rhodes, and Madeleine Yi, 2022, Bill of lading data in international trade research with an application to the COVID-19 pandemic, Review of International Economics pp. 1146–1172.

Gagliardone, Luca, Mark Gertler, Simone Lenzu, and Joris Tielens, 2023, Anatomy of the Phillips Curve: Micro Evidence and Macro Implications, Working Paper.

Gertler, Mark, and Simon Gilchrist, 1994, Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms, The Quarterly Journal of Economics 109, 309–340.

Grullon, Gustavo, Yelena Larkin, and Roni Michaely, 2019, Are us industries becoming more concentrated?, Review of Finance 23, 697–743.

Gutiérrez, Germán, and Thomas Philippon, 2019, Fading Stars, AEA Papers and Proceedings 109, 312–316.

——— , 2021, Some Facts About Dominant Firms, Working Paper.

Hansen, Niels-Jakob, Frederik Toscani, and Jing Zhou, 2023, Euro Area Inflation after the Pandemic and Energy Shock: Import Prices, Profits and Wages, IMF Working Papers.

Inderst, Roman, and Christian Wey, 2007, Buyer Power and Supplier Incentives, European Economic Review 51, 647–667.

Kemp, Harri, Rafael Portillo, and Marika Santoro, 2023, Assessing the Impact of Supply Disruptions on the Global Pandemic Recovery, IMF Working Papers.

Klein, Benjamin, Robert G. Crawford, and Armen A. Alchian, 1978, Vertical Integration, Appropriable Rents, and the Competitive Contracting, The Journal of Law and Economics 21, 297–326.

Konczal, Mike, and Niko Lusiani, 2022, Prices, Profits, and Power: An Analysis of 2021 Firm-Level Markups, Working Paper.

Syverson, Chad, 2019, Macroeconomics and Market Power: Context, Implications, and Open Questions, Journal of Economic Perspectives 33, 23–43.

Williamson, O, 1979, Transaction-Cost Economics: The Governance of Contractual Relations, The Journal of Law and Economics 22, 233–261.

A Proof of Proposition 1

Proof. A firm's profit maximization problem is

$$\underset{q_i}{Max} \pi_i = p\left(Q\right) q_i - c_i q_i$$

with first order condition

$$p\left(Q\right) + \frac{\partial p}{\partial Q} q_i - c_i = 0. \tag{A.1}$$

Using the demand function in Equation (4), the first order condition becomes

$$b - \sum_{j=1}^{n} q_j - q_i - c_i = 0. \tag{A.2}$$

To find the solution, we first sum Equation (A.2) across all n firms to obtain

$$\sum_{j=1}^{n} q_j = \frac{nb - \sigma}{1+n}. \tag{A.3}$$

Then, we replace Equation (A.3) into Equation (A.2) and obtain

$$q_i = \frac{b + \sigma - \left(1+n\right) \delta_i c}{1+n}. \tag{A.4}$$

Using the aggregate equilibrium quantity, Equation (A.3), and the demand function, Equation (4), we can compute the equilbrium price

$$p = \frac{b+\sigma}{1+n}. \tag{A.5}$$

From Equation (A.5), it is evident that prices in the industry increase following an increase in supply chain shortages. The increase in price is as if all firms were equally exposed. However, as we show below, the firms with larger market shares are less exposed to the increase in σ. To see this, we use Equations (A.4) and (A.3) and compute the market share of firm i as

$$s_i = \frac{q_i}{\sum\limits_{j=1}^{n} q_j} = \frac{b + \sigma - \left(1+n\right) \delta_i \sigma}{nb - \sigma}. \tag{A.6}$$

We are now in the position to prove that an increase in the marginal costs for all producers leads to an increase in market share for low-cost firms and a decrease in market share for high-cost firms. We take the first order derivative of the market share in Equation (A.6) with respect to σ

$$\frac{\partial s_i}{\partial \sigma} = \frac{nb - (1+n)\, nb\delta_i + b}{(nb-\sigma)^2}.$$

Then, we have that

$$\frac{\partial s_i}{\partial \sigma} > 0 \quad \text{iff} \quad \delta_i < \frac{1}{n}.$$

In other words, firm i experiences an increase in market share when marginal costs increase for all firms if and only if the marginal cost of firm i is below the average marginal cost in the industry (remember that $\sum_{j=1}^{n} \delta_j = 1$).

Following an increase in industry costs, firms that benefit from an increase in market share – i.e. low-cost firms – will experience higher markups. To verify this claim, it is sufficient to define the markup as

$$\frac{p - c_i}{p}$$

and to use the first order condition in Equation (A.1) to show that

$$\frac{p - c_i}{p} = \frac{s_i}{|\varepsilon|}, \tag{A.7}$$

where $\varepsilon = \frac{\partial p}{\partial Q}\frac{Q}{p}$ is the inverse elasticity of demand. □

B Proof of Proposition 2

Proof. To this purpose, it is enough to show that the second derivative of the market share of each firm with respect to σ is positive.

$$\frac{\partial^2 s_i}{\partial^2 \sigma} = 2\frac{nb - (1+n)\, nb\delta_i + b}{(nb-\sigma)^3},$$

which is positive under the parametric assumptions that we have made to obtain positive individual firms' output and aggregate output (see footnote 11).

Based on the sign of this second derivative, an increase in costs will have a higher impact on the dispersion in market shares the higher the starting level of the cost dispersion. Thus, for higher levels of HHI, which correspond to a higher dispersion of the δ_i, the impact of supply chain shortages on the industry concentration is larger. $\square$

C Solution of the Model with Heterogeneous Products

The demand function for firm i's good depends on i's quantity as well as the other $n-1$ firms' quantities Q_{-1}

$$p_i\left(q_i, Q_{-i}\right) = b_i - q_i - kQ_{-i}, \tag{A.8}$$

where the parameter k captures the substitutability between firm i's products and the other firms' products.

The profit function for firm i is

$$\pi\left(q_i, Q_{-i}\right) = \left(b_i - q_i - kQ_{-i} - c_i\right) q_i. \tag{A.9}$$

Differentiation Equation (A.9) with respect to q_i gives the F.O.C.

$$b_i - 2q_i - kQ_{-i} - c_i = 0. \tag{A.10}$$

Summing Equation (A.10) over $j \neq i$, we can find an expression for Q_{-i}

$$Q_{-i} = \frac{\sum_{j\neq i}\left(b_j - c_j\right)}{2 + (n-1)\,k}. \tag{A.11}$$

Then, replacing the expression from Equation (A.11) into Equation (A.10), we find the equilibrium quantity for firm i

$$q_i = \frac{b_i - c_i}{2} - \frac{k}{2}\frac{\sum_{j\neq i}\left(b_j - c_j\right)}{2 + (n-1)\,k}. \tag{A.12}$$

It is evident from Equation (A.12) that a demand shock affecting the parameter b_i has equivalent implications to a cost shock affecting the parameter c_i, as claimed in the main text.

Figures

Figure 1
The Time-Series of Supply Chain Shortages

This figure plots the time-series of the average of our proxies for supply chain disruption across U.S. industries. We report Industry Exposure Delays on the left y-axis and Delivery Time on the right y-axis.

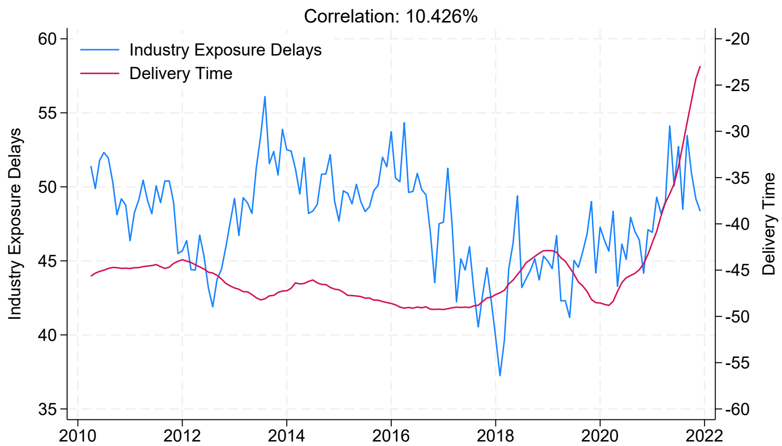
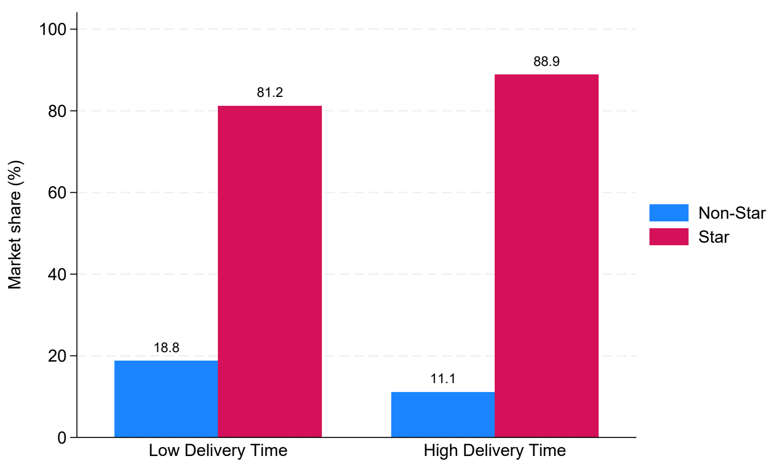
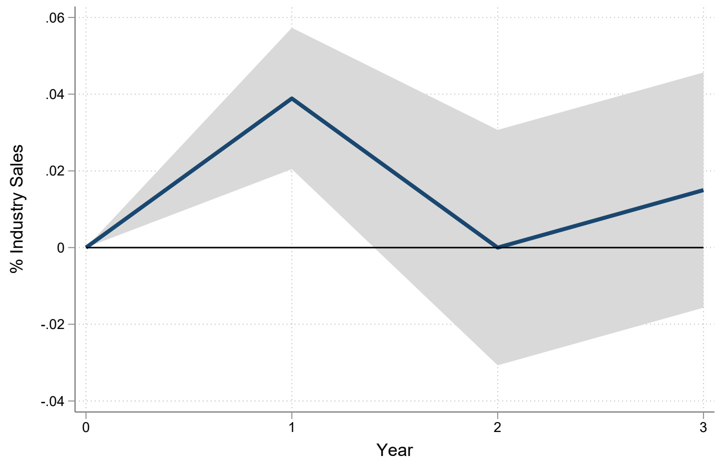


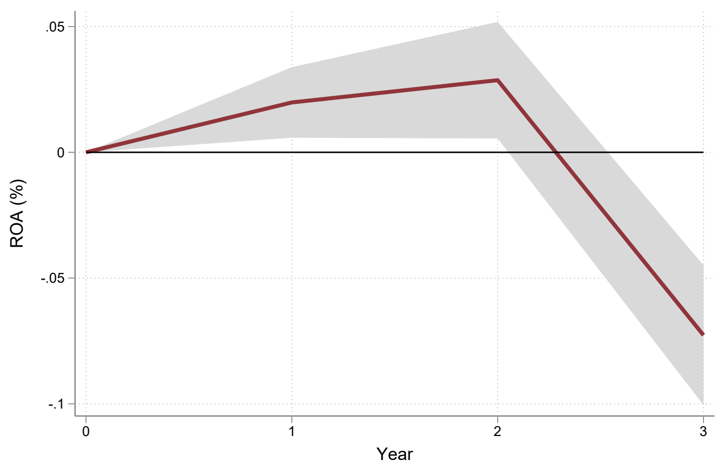
Figure 2
Market Share and Delivery Time

This figure plots the average total market share of Star and Non-Star firms in periods of low and high delivery time. At the top of each bar we report the percentage market share for each group.





(a) Change in % Industry Sales



(b) Change in ROA (%)

Figure 3
Dynamic Effects

This figure plots the β_1 for the following regression run for $h = 1, 2, 3$:

$$dy_{i,[t+h,t+h-1]} = \alpha_{j,c,t} + \beta_1 Delivery\ Time_{j,t} \times Star_{i,t} + \beta_2 Star_{i,t} + \varepsilon_{i,t},$$

where $dy_{i,[t+h,t+h-1]}$ is either the change in % industry sales or the change in ROA, defined between year $t+h$ and $t+h-1$. $DeliveryTime$ is defined in the 12 months before the end of year t for industry j to which firm i belongs. $\alpha_{j,c,t}$ represent industry-by-country-by-year fixed effects. The levels of $DeliveryTime$ are subsumed by the fixed effects. The shaded area represents the 95% confidence interval for standard errors clustered at the firm level.

Tables

Table 1
Variables Description

Variable	Description
	Firm-level variables
% Industry Sales	Market share of a 2-digit SIC industry sales held by a firm at the end of the year.
Markup	Sales/Variable Input, where Operating Expenses* (OPEX*) is used as a variable input. OPEX* is defined as operative expenses (ITEM1249) - R&D (ITEM1201) - R&D Amortization (ITEM1152) - 0.3*Net SG&A (ITEM1101-ITEM1201). Missing values of R&D, R&D Amortization and SG&A are set to zero. Note: Ayyagari, et al., 2023 subtract in-process R&D (rdip in Compustat), however this variable is not available in Worldscope and we replace it with R&D Amortization.
ROA	Π_{it}/A_{it}, where Π_{it} is profit defined as $(S_{it} - P^V_{it} V_{it} - r_t K_{it} - P^X_t X_{it})$. S_{it} represents sales (ITEM7240); A_t is total assets (ITEM7230); $P^X_t X_{it}$ is SG&A (ITEM1101); $P^V_{it} V_{it}$ is variable input measured using COGS (ITEM1051); $r_t K_{it}$ is the user cost of capital multiplied by the capital stock (PPEGT, ITEM2301). The user cost of capital is defined as nominal interest rate minus inflation rate minus depreciation rate. The nominal interest rate is the fed funds rate, the inflation rate is the percentage change in CPI, and the depreciation rate is set to 12% as in De Loecker, Eeckhout, and Unger (2020). We drop observations with non-positive sales and total assets. All variables are in USD and deflated using the US GDP deflator at 2009 prices.
Average Interest Rate	Dummy equal to 1 if the firm's average interest rate (Worldscope's item 08356) is in the top tercile of the country-level distribution in year t-1 (computed in the full Worldscope sample).
Cash Available	Dummy equal to 1 if the firm's cash and short term investments (Worldscope's item 02001) divided by total assets is in the top tercile of the country-level distribution in year t-1 (computed in the full Worldscope sample).
Inventory	Ratio of inventories (Worldscope's item 02101) to sales in year t-1.
Delta COGS	Year-to-year percentage change in COGS (ITEM1051).
Raw returns	Monthly stock returns from Datastream expressed in basis points.
Abnormal returns	Monthly abnormal returns computed by subtracting the monthly return on the MSCI Developed index from a firm's monthly stock returns. Expressed in bps.
Star	Dummy equal to 1 if the firm is in top 10% of sales distribution within a 2-digit sic industry in year t-1. Computed for the entire universe of Worldscope firms.

Table 1
Variables Description (continued)

Delivery Time	Previous 12-month average supplier delivery time. The index is defined as (percentage of survey panel responding "Faster") + (percentage responding "Same"*0.5). Readings of 50 indicate no change in delivery times on the prior month, readings above 50 indicate that delivery times have improved (become shorter, or faster) and readings below 50 indicate that delivery times have deteriorated (become longer, or slower). We multiply this variable by -1 to keep the interpretation equal to that of Mean Backlog.
Industry Exposure Delays	For each 2-digit SIC industry i and month t, we define the *Industry Exposure Delays* as $$100 \times \sum_j Industry\ Exposure_{i,j} \times (slower\_port_{j,t} + 0.5 \times same\_transit\_time\_port_{j,t})$$ where *slower_port* is a dummy denoting a port whose average transit time has increased by more than five days vis-a-vis the previous month, and *same_transit_time_port* is a dummy denoting a port whose transit times are within a range of -5 to +5 days relative to the previous month. *Industry Exposure* is the fraction of a 2-digit industry's shipments from a given port at the beginning of the sample. We use the average of the variable in previous 12 months.
	Industry-level variables
Industry CPI (% YoY, monthly freq.)	Annual change in monthly consumer price index for a relevant industry in a country.
HHI (Sales)	Herfindahl-Hirschman Index of sales for a 2-digit SIC industry (defined at sample start for each country).
CR4 (Sales)	Fraction of a 2-digit SIC industry held by the top 4 firms (defined at sample start for each country).
% Sales of Stars	% of the total sales in a 2-digit SIC industry-country-year attributable to star firms.
Dummy Has Star	Indicator equal to 1 if a country-industry-year has at least one star firm.
Delta COGS	Year-to-year percentage change in total COGS (ITEM1051) in an industry-country.
	Shipment-level variables
1(Trade > 0)	Indicator for shipments greater than zero in a supplier-customer-quarter tuple.
Containers	Number of containers shipped by a supplier to a customer in given quarter.
Shipments	Number of shipments between a supplier and a customer in a given quarter.
Weight	Weight of goods shipped (in tons) by a supplier to a customer in a given quarter.
Volume	Volume in TEUs (twenty-foot equivalent units) of supplier-to-customer shipments in a quarter.
Quantity	Number of unique items (in 1,000s) shipped by a supplier to a customer in a quarter.

Table 2
Summary Statistics

See Table 1 for variables definitions. All variables are winsorized at the 1% and 99%.

Panel A	Firm-level variables							
	No. obs	Mean	Std	Min	p25	Median	p75	Max
% Industry Sales	77,500	0.259	0.761	0.000	0.006	0.030	0.145	6.587
Change in % Industry Sales	77,239	0.001	0.072	-0.436	-0.002	0.000	0.003	0.470
Log Markups	76,610	0.089	0.458	-2.834	0.057	0.131	0.230	1.014
Markups	76,632	1.166	0.331	0.054	1.058	1.140	1.258	2.757
Change in Markups	75,810	0.004	0.153	-0.688	-0.028	0.001	0.031	0.753
ROA	71,425	2.097	15.769	-81.353	-2.156	3.314	9.000	45.888
Change in ROA	69,865	0.082	8.427	-37.459	-2.342	0.027	2.408	38.136
Average Interest Rate	66,517	0.267	0.442	0.000	0.000	0.000	1.000	1.000
Cash Available	77,179	0.270	0.444	0.000	0.000	0.000	1.000	1.000
Inventory	63,813	18.048	20.417	0.000	8.232	13.765	21.230	187.670
Delta COGS	75,719	0.089	0.415	-0.814	-0.078	0.032	0.164	2.798
Star	77,500	0.239	0.427	0.000	0.000	0.000	0.000	1.000
Delivery Time	77,500	-46.400	4.804	-51.481	-49.004	-47.631	-45.695	-22.848
Port Arrival Time	77,484	47.498	5.418	26.842	44.944	48.595	51.068	58.691
Raw Returns (bps)	629,427	87.311	1,419.649	-3,632	-675.204	-4.471	697.079	5,556
Abnormal Returns (bps)	629,427	-49.871	1,371.169	-3,743	-809.053	-147.372	565.738	5,247
Panel B	**Industry-level variables**							
	No. obs	Mean	Std	Min	p25	Median	p75	Max
Industry CPI (% YoY, monthly frequency)	74,837	1.647	6.732	-53.600	-0.400	1.300	3.300	193.700
CR4 (Sales)	74,837	0.922	0.167	0.430	0.971	1.000	1.000	1.000
HHI (Sales)	74,837	0.695	0.354	0.076	0.364	1.000	1.000	1.000
% Sales of Stars	72,131	66.905	37.587	0.000	49.679	86.241	95.029	100.000
Dummy Has Star	72,131	0.788	0.409	0.000	1.000	1.000	1.000	1.000
Delivery Time	49,567	-47.067	3.331	-54.322	-49.081	-47.983	-46.263	-16.858
Delta COGS	72,035	0.085	0.117	-0.254	0.023	0.074	0.127	0.557
Panel C	**Shipment-level variables**							
	No. obs	Mean	Std	Min	p25	Median	p75	Max
1(Trade >0)	232,611	0.418	0.493	0.000	0.000	0.000	1.000	1.000
Containers	232,611	4.750	12.332	0.000	0.000	0.000	3.000	64.000
Shipments	232,611	3.052	7.198	0.000	0.000	0.000	2.000	36.000
Weight (tons)	232,611	107.123	377.995	0.000	0.000	0.000	14.960	1,909.190
Volume (TEU)	232,611	6.423	18.592	0.000	0.000	0.000	2.000	98.750
Quantity (1,000s)	232,611	3.409	10.803	0.000	0.000	0.000	0.618	58.270

Table 3
Characteristics of Superstars' Suppliers

Columns (1) and (2) show results of a regression where the outcome variable represents a feature of a firm's supply chain and the main explanatory variable is our indicator for "superstar" firms. In column (1), the dependent variable is the fraction of suppliers from the same country of the customer firm, while in column (2) we use the average number of suppliers in a 2-digit sic industry. The sample is at the firm-year level and each specification include customer firm's (C) industry-by-country-by-year fixed effects. In columns (3) and (4) the sample is instead at the customer-supplier-year level. Here, the dependent variable is an indicator for star suppliers, and we include combinations of different customer-by-supplier (CS) firm fixed effects, as well as industry, country, and year fixed effects (FE). Star is a dummy equal to 1 if a firm is in the top decile of the sales distribution. All continuous variables are standardized by subtracting the mean and dividing for the standard deviation. Standard errors are reported in parentheses and clustered at the firm level in columns (1)-(2), and at the customer-by-year level in columns (3)-(4). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Fraction of home suppliers	N. of suppliers per industry	$Star^S$	
	(1)	(2)	(3)	(4)
$Star^C$	-0.035***	2.670***	0.007***	0.005***
	(0.006)	(0.157)	(0.002)	(0.002)
$Size^C$				0.004*
				(0.002)
$Size^S$				0.185***
				(0.003)
C Industry-Country-Year FE	Yes	Yes	No	No
Year FE	No	No	Yes	Yes
CS-Firm FE	No	No	Yes	Yes
CS-Industry FE	No	No	Yes	Yes
CS-Country FE	No	No	Yes	Yes
Obs.	67,548	67,548	762,724	691,513
Adj. R2	0.242	0.140	0.926	0.934

Table 4
Supply Chains Shortages and Quantities Shipped

This table shows results of an OLS regression where the outcome variable is one of our proxy for shipment quantity and the main explanatory variable is the interaction between *Star* dummy and *Delivery Time*. The sample is at the customer-supplier-quarter level. We create an extended panel for each customer-supplier pair as follows. First, we require the supplier-customer relationship to appear in at least two distinct years during our sample period. Second, we create a full panel including observations in all quarters within the start and the end of the relationship. All transaction values are set to zero for all the quarters in which transaction values are missing between the first and the last relationship quarter. Third, we require that a given customer-quarter observation is available in Compustat quarterly. *Star* is a dummy equal to 1 if a firm is in the top 10% of sales in the annual Compustat file in year $t-1$. *Delivery Time* is averaged within a customer's 2-digit SIC industry in the past 12-months before the quarter end. All variables are defined in Table 1. In Panel A, we run regressions using an OLS model, while we use a Poisson model in Panel B. *Delivery Time* is standardized by subtracting the mean and dividing for the standard deviation. Standard errors are clustered at the customer-by-year-quarter level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A	OLS regressions					
Dependent variable	1(Trade > 0)	Containers	Shipments	Weight	Volume	Quantity
	(1)	(2)	(3)	(4)	(5)	(6)
Star × Delivery Time	0.020**	0.981***	0.364*	16.478***	1.306***	1.167***
	(0.010)	(0.315)	(0.188)	(6.267)	(0.453)	(0.280)
Star	-0.067***	0.816**	0.683***	16.996***	0.636	0.010
	(0.013)	(0.336)	(0.210)	(4.663)	(0.467)	(0.280)
Supplier-Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm's Industry-Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	225,453	225,453	225,453	225,453	225,453	225,453
Adj. R2	0.134	0.144	0.121	0.226	0.170	0.135

Table 4
Supply Chains Shortages and Quantities Shipped (continued)

Panel B	Poisson regressions				
Dependent variable	Containers	Shipments	Weight	Volume	Quantity
	(1)	(2)	(3)	(4)	(5)
Star × Delivery Time	0.168***	0.093***	0.103***	0.175***	0.356***
	(0.035)	(0.032)	(0.031)	(0.036)	(0.052)
Star	0.151***	0.201***	0.127***	0.088	-0.015
	(0.054)	(0.050)	(0.029)	(0.059)	(0.070)
Supplier-Year-Qtr FE	Yes	Yes	Yes	Yes	Yes
Firm's Industry-Year-Qtr FE	Yes	Yes	Yes	Yes	Yes
Obs.	163,348	163,348	163,299	147,874	163,348
Pseudo R2	0.499	0.436	0.678	0.548	0.582

Table 5
Supply Chains Shortages and Quantities Shipped: Industry Exposure Delays

This table shows results of a 2SLS version of Table 4, where *Star* $\times$ *Delivery Time* is instrumented by *Star* $\times$ *Industry Exposure Delays*. Standard errors are clustered at the customer-by-year-quarter level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Sample	2019-2021					
	First stage	Second stage				
Dependent variable	Star × Delivery Time	Containers	Shipments	Weight	Volume	Quantity
	(1)	(2)	(3)	(4)	(5)	(6)
Star × Industry Exposure Delays	0.448***					
	(0.065)					
Star × Delivery Time		2.916***	1.652***	69.791***	3.510***	2.389***
		(0.855)	(0.496)	(21.884)	(1.200)	(0.695)
Star	1.029***	0.903	0.307	-9.736	0.828	0.851
	(0.113)	(0.925)	(0.546)	(22.109)	(1.140)	(0.742)
Supplier-Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm's Industry-Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic	46.777					
Obs.	39,991	39,991	39,991	39,991	39,991	39,991

Table 6
Superstar Firms' Market Share and Profitability

Star is a dummy equal to 1 if a firm is above the 90th percentile of the sales distribution at the beginning of a given year within a 2-digit sic industry. Industry is based on 2-digit sic codes. In columns (1)-(4), the dependent variables are in levels, while we use year-on-year changes in columns (5)-(8). A definition of all variables can be found in Table 1. All continuous variables are standardized by subtracting the mean and dividing for the standard deviation. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Levels of dependent variable				Year-on-year changes of dependent variable			
Dependent variable	% Industry Sales		ROA (%)		Delta % Industry Sales		Delta ROA (%)	
	Full sample	2019-2021	Full sample	2019-2021	Full sample	2019-2021	Full sample	2019-2021
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Star × Delivery Time	0.037***	0.041***	0.079***	0.074***	0.039***	0.049***	0.020**	0.029***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.014)	(0.009)	(0.011)
Star	0.709***	0.672***	0.365***	0.324***	-0.002	0.024	-0.004	-0.028**
	(0.025)	(0.024)	(0.018)	(0.018)	(0.012)	(0.020)	(0.006)	(0.012)
Industry-Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	77,500	28,051	71,061	25,725	77,219	28,012	69,426	24,973
Adj. R2	0.472	0.462	0.168	0.173	0.186	0.168	0.084	0.147

Table 7
Industry Exposure Delays: 2-Stage Least Squares

This table reports results for 2-stage least squares regressions where the interaction of Star and Industry Exposure Delays is used as instrument for the interaction of Star and Delivery time. We consider the full sample in columns (1)-(4), and the period 2019-2021 in columns (5)-(8). Columns (1) and (5) report the first stage results, while columns (2)-(4) and (6)-(8) report coefficients for the second stage regressions where the dependent variable is percentage of industry sales, ROA, and markup, respectively. Continuous variables are standardized by subtracting the sample mean and dividing by the sample standard deviation. Standard errors are clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Full sample				2019-2021			
	First stage	Second stage			First stage	Second stage		
Dependent variable	Star × Delivery Time	% Industry Sales	ROA (%)	Log-Markups	Star × Delivery Time	% Industry Sales	ROA (%)	Log-Markups
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Star × Industry Exposure Delays	0.026***				0.639***			
	(0.009)				(0.061)			
Star × Delivery Time		2.189*	3.939**	1.755*		0.154**	0.220***	0.206***
		(1.188)	(1.703)	(1.008)		(0.073)	(0.066)	(0.060)
Star	0.362***	-0.194	-0.620	-0.144	1.561***	0.443***	0.529***	0.311***
	(0.009)	(0.424)	(0.620)	(0.366)	(0.022)	(0.094)	(0.109)	(0.102)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F statistic	7.921				109.755			
Obs.	14,598	14,598	13,973	14,515	3,726	3,726	3,571	3,726

Table 8
Supply Chain Shortages and Markups

We define markups as in Ayyagari, Demirguc-Kunt, and Maksimovic (2023). See Table 1 for a detailed definition. In column (1)-(2) we take the logarithm of the markup, while columns (3)-(4) and (5)-(6) use the level and the first difference of markup, respectively. Delta COGS is defined as the year-on-year percentage change in COGS (ITEM1051). All continuous variables are standardized by subtracting the mean and dividing by the standard deviation. Standard errors reported in parentheses are clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Markups					
Dep. var. definition.	Log		Levels		Changes	
	Full sample	2019-2021	Full sample	2019-2021	Full sample	2019-2021
	(1)	(2)	(3)	(4)	(5)	(6)
Star × Delivery Time	0.058***	0.042***	0.069***	0.053***	0.023***	0.027**
	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.011)
Star × Delta COGS	0.037**	0.031	0.049***	0.023	-0.227***	-0.247***
	(0.014)	(0.027)	(0.019)	(0.032)	(0.019)	(0.034)
Delta COGS	0.002	0.018	0.015**	0.032***	0.100***	0.134***
	(0.009)	(0.015)	(0.007)	(0.012)	(0.010)	(0.015)
Star	0.270***	0.285***	0.235***	0.242***	-0.031***	-0.025**
	(0.015)	(0.020)	(0.018)	(0.021)	(0.006)	(0.012)
Industry-Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	74,735	27,516	74,754	27,523	74,164	27,521
Adj. R2	0.178	0.197	0.139	0.143	0.100	0.133

Table 9
Percentage Change in COGS

This table repeats the main firm-level analysis of Table 6 using as dependent variable the year-on-year percentage change in COGS. All continuous variables are standardized by subtracting the mean and dividing for the standard deviation. Standard errors reported in parentheses are clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	% Change in COGS	
	Full Sample	2019-2021
	(1)	(2)
Star × Delivery Time	-0.022**	-0.022**
	(0.009)	(0.010)
Star	-0.149***	-0.115***
	(0.008)	(0.013)
Industry-Country-Year FE	Yes	Yes
Obs.	75,675	27,546
Adj. R2	0.082	0.100

Table 10
Stock Returns

The dependent variable is a firm's monthly raw return (columns (1)-(4)), or the monthly abnormal return (columns (5)-(8)). Both variables are expressed in basis points (bps). Stock returns are from Datastream. Abnormal returns are computed by subtracting the monthly return on the MSCI Developed index from a firm's monthly stock return. In columns (1)-(2) and (5)-(6) we consider the full sample (2010-2021), while in columns (3)-(4) and (7)-(8) we focus on the period 2019-2021. We report in parentheses standard errors clustered at the stock and calendar month level in the full sample specifications and at the stock level only in the 2019-2021 sample. The single clustering for the 2019-2021 sample is justified by the small size of the time dimension which accounts for 36 months only. Delivery Time is standardized by subtracting the mean and dividing by the standard deviation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Raw returns (bps)				Abnormal returns (bps)			
	Full sample		2019-2021		Full sample		2019-2021	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Star × Delivery Time	23.073**	25.402**	32.021***	35.354***	22.735**	24.947**	32.143***	35.341***
	(10.157)	(10.411)	(4.288)	(5.043)	(10.086)	(10.351)	(4.291)	(5.047)
Star	18.829*	17.895*	8.636	4.120	19.295**	18.444*	6.461	2.284
	(9.957)	(10.100)	(6.565)	(7.316)	(9.744)	(9.890)	(6.540)	(7.318)
Delivery Time	4.392		22.970**		4.078		23.022**	
	(10.176)		(11.294)		(10.219)		(11.295)	
Industry-Month FE	Yes	No	Yes	No	Yes	No	Yes	No
Country-Month FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry-Country-Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	678,832	629,427	258,199	243,675	678,832	629,427	258,199	243,675
Adj. R2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 11
Delta HHI

The dependent variable is the first difference of sales HHI constructed for each industry-country-year between t and $t+1$ and is regressed on the HHI at the beginning of the sample. Industry is based on 2-digit SIC codes. A definition of all other variables can be found in Table 1. All continuous variables are standardized by subtracting the mean and dividing for the standard deviation. Standard errors are clustered at the industry level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Delta HHI			
	(1)	(2)	(3)	(4)
Delivery Time × Ex-Ante HHI	0.027***	0.023***	0.023***	0.035***
	(0.006)	(0.007)	(0.007)	(0.008)
Delivery Time	0.018	-0.024	-0.022	-0.020
	(0.011)	(0.016)	(0.017)	(0.018)
Ex-Ante HHI	-0.101***	-0.104***	-0.111***	
	(0.007)	(0.008)	(0.008)	
Year FE	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	No
Industry FE	No	No	Yes	No
Country-Industry FE	No	No	No	Yes
Obs.	8,712	8,710	8,710	8,635
Adj. R2	0.011	0.008	0.009	0.001

Table 12
Change in Industry Sales

The dependent variable is the growth rate of sales for each industry-country-year between t and $t+1$ and is regressed on the HHI at the beginning of the sample. Industry is based on 2-digit SIC codes. A definition of all other variables can be found in Table 1. All continuous variables are standardized by subtracting the mean and dividing for the standard deviation. Standard errors are clustered at the industry level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Sales growth rate			
	(1)	(2)	(3)	(4)
Delivery Time × Ex-Ante HHI	-0.021*	-0.017	-0.018*	-0.018**
	(0.011)	(0.010)	(0.010)	(0.009)
Delivery Time	-0.008	0.042***	0.046***	0.045**
	(0.011)	(0.015)	(0.015)	(0.017)
Ex-Ante HHI	0.072***	0.054***	0.059***	
	(0.011)	(0.012)	(0.011)	
Year FE	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	No
Industry FE	No	No	Yes	No
Country-Industry FE	No	No	No	Yes
Obs.	8,675	8,673	8,673	8,602
Adj. R2	0.005	0.003	0.003	0.001

Table 13
Supply Chain Shortages and Industry Inflation

In Panel A, we run our baseline specification on the full sample of countries. In Panel B, we use alternative definitions of industry concentration. CR4 is computed for each country and 2-digit SIC code at the beginning of the sample at the country-industry level. The variables in columns (3)-(6) are defined at the country-industry-year in year t-1. Finally, in Panel C we repeat the analysis for the subsamples of industries in the United States, and Europe. Europe comprises the Euro-area plus Denmark, Norway, Switzerland and the United Kingdom. All continuous independent variables are standardized by subtracting the mean and dividing for the standard deviation. Industry is proxied by 2-digit sic codes. A definition of all variables can be found in Table 1. Standard errors are adjusted for clusters at the year-month level and 11 lags of autocorrelation and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A	Main analysis			
Dependent variable	Industry CPI (% YoY, monthly frequency)			
	Full sample	2019-2021	Full sample	2019-2021
	(1)	(2)	(3)	(4)
Delivery Time × Ex-Ante HHI	0.680**	1.162***	0.907***	1.348***
	(0.304)	(0.305)	(0.316)	(0.209)
Delivery Time	1.486**	2.600***	2.622***	3.763***
	(0.727)	(0.648)	(0.841)	(0.510)
Delta COGS × Ex-Ante HHI			0.387***	0.994
			(0.147)	(0.697)
Delta COGS			1.885***	4.550**
			(0.524)	(2.008)
Country-Industry-Year FE	Yes	Yes	No	No
Year-Month FE	Yes	Yes	Yes	Yes
Country-Industry FE	No	No	Yes	Yes
Obs.	60,820	19,700	48,664	13,997
Adj. R2	0.584	0.631	0.195	0.221

Table 13
Supply Chain Shortages and Industry Inflation (continued)

Panel B	Alternative measures of concentration					
Dependent variable	Industry CPI (% YoY, monthly frequency)					
Industry variable	CR4 Sales		% Sales of Stars		Dummy Has Star	
	Full sample	2019-2021	Full sample	2019-2021	Full sample	2019-2021
	(1)	(2)	(3)	(4)	(5)	(6)
Delivery Time × Industry Structure	0.470**	0.763***	0.940***	1.034***	2.156***	2.320**
	(0.208)	(0.188)	(0.292)	(0.380)	(0.737)	(0.974)
Delivery Time	1.410**	2.381***	1.053***	1.288***	-0.554	-0.427
	(0.684)	(0.586)	(0.329)	(0.385)	(0.698)	(0.995)
Country-Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	60,820	19,700	53,525	18,702	53,525	18,702
Adj. R2	0.584	0.630	0.603	0.635	0.603	0.635

Table 13
Supply Chain Shortages and Industry Inflation (continued)

Panel C	Geographic split			
Dependent variable	Industry CPI (% YoY, monthly frequency)			
	US		Europe	
	Full sample	2019-2021	Full sample	2019-2021
	(1)	(2)	(3)	(4)
Delivery Time × Ex-Ante HHI	0.965***	1.148***	1.286***	1.342**
	(0.346)	(0.323)	(0.475)	(0.616)
Delivery Time	3.106	4.466	2.847*	5.986***
	(5.316)	(8.888)	(1.596)	(2.103)
Country-Industry-Year FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Obs.	11,627	3,715	20,512	5,688
Adj. R2	0.551	0.530	0.702	0.738

Internet Appendix

Table A1
Superstar Firms' Market Share, Profitability, and Markup: Industry Exposure Delays

This table reports results for the reduced form regression of Table 7. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	% Industry Sales		ROA (%)		Log-Markups (%)	
	Full sample	2019-2021	Full sample	2019-2021	Full sample	2019-2021
	(1)	(2)	(3)	(4)	(5)	(6)
Star × Industry Exposure Delays	0.057**	0.098**	0.100***	0.141***	0.047**	0.132***
	(0.025)	(0.047)	(0.025)	(0.039)	(0.022)	(0.035)
Star	0.599***	0.683***	0.815***	0.872***	0.494***	0.633***
	(0.043)	(0.070)	(0.045)	(0.053)	(0.038)	(0.053)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	14,598	3,726	13,973	3,571	14,515	3,726
Adj. R2	0.386	0.293	0.212	0.214	0.062	0.059

Table A2
Alternative Measures of Firms' Markups

Different from Table 8, this table defines markups by scaling sales by total costs (COGS+SG&A+KEPX) as in De Loecker, Eeckhout, and Unger (2020) (columns (1)-(4)), or by OPEX not adjusted for SG&A and R&D (columns (5)-(8)). We report results on the full sample, and the period 2019-2021, separately. All continuous variables are standardized by subtracting the mean and dividing for the standard deviation. Standard errors reported in parentheses are clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Markups (De Loecker, et al., 2020)				Markups (OPEX)			
Dep. var. definition.	Log		Levels		Log		Levels	
	Full sample	2019-2021	Full sample	2019-2021	Full sample	2019-2021	Full sample	2019-2021
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Star × Delivery Time	0.088***	0.078***	0.093***	0.088***	0.022***	0.019***	0.057***	0.052***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.003)	(0.003)	(0.005)	(0.005)
Star	0.375***	0.367***	0.335***	0.326***	0.089***	0.087***	0.159***	0.136***
	(0.017)	(0.020)	(0.017)	(0.019)	(0.005)	(0.006)	(0.009)	(0.009)
Industry-Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	70,105	25,436	70,110	25,438	76,543	28,021	76,553	28,023
Adj. R2	0.158	0.165	0.168	0.172	0.937	0.936	0.839	0.832

Table A3
Placebo: Energy Prices Shocks

Energy Shock is proxied by the year-over-year percentage change in the Global Energy Price Index (FRED variable PNRGINDEXM). Industry Emissions is the average GHG scope 1 and scope 2 emission intensity from Trucost. All continuous variables are standardized by subtracting the mean and dividing by the standard deviation. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	% Industry Sales		ROA (%)	
	(1)	(2)	(3)	(4)
Energy Shock × Star	0.006	0.006	0.009	0.009
	(0.005)	(0.005)	(0.006)	(0.006)
Star	0.802***	0.804***	0.399***	0.396***
	(0.028)	(0.028)	(0.019)	(0.019)
Energy Shock × Industry Emissions × Star		-0.002		0.007
		(0.005)		(0.006)
Industry Emissions × Star		0.040		-0.055***
		(0.029)		(0.012)
Industry-Country-Year FE	Yes	Yes	Yes	Yes
Obs.	77,500	77,500	71,061	71,061
Adj. R2	0.472	0.472	0.167	0.167

Table A4
Financing Constraints

In columns (1)-(4), financing constraints is a dummy equal to 1 if the firm's average interest rate is in the top tercile of the country-level distribution in year t-1. The variable is defined as Interest Rate on Debt/(Short Term Debt & Current Portion of Long Term Debt+Long Term Debt)*100. In columns (5)-(8) we proxy for financing constraints with a dummy equal to 1 if the firm's cash-to-asset ratio is in the top tercile of the country-level distribution in year t-1. Cash is measured as cash and short term investment (ITEM2001). All continuous variables are standardized by subtracting the mean and dividing for the standard deviation. Standard errors reported in parentheses are clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Financing Constr. Proxy	Average interest rate				Cash available			
Dependent variable	% Industry Sales		ROA (%)		% Industry Sales		ROA (%)	
	Full sample	2019-2021	Full sample	2019-2021	Full sample	2019-2021	Full sample	2019-2021
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Star × Delivery Time	0.030***	0.035***	0.060***	0.062***	0.037***	0.042***	0.049***	0.045***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.008)	(0.008)
Financing Constr. × Delivery Time	-0.018***	-0.015**	-0.058***	-0.046***	0.003	0.007	-0.160***	-0.156***
	(0.006)	(0.006)	(0.011)	(0.012)	(0.005)	(0.005)	(0.014)	(0.015)
Financing Constr.	-0.061***	-0.041***	-0.188***	-0.165***	-0.007	-0.007	-0.113***	-0.039**
	(0.010)	(0.010)	(0.013)	(0.015)	(0.009)	(0.008)	(0.018)	(0.020)
Star	0.699***	0.663***	0.300***	0.255***	0.708***	0.672***	0.347***	0.317***
	(0.025)	(0.024)	(0.016)	(0.016)	(0.025)	(0.024)	(0.017)	(0.017)
Industry-Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	66,165	24,938	61,477	23,102	77,158	27,994	70,805	25,692
Adj. R2	0.478	0.470	0.173	0.176	0.472	0.462	0.175	0.184

Table A5
Firms' Operational Resilience and Inventories

Inventory is the ratio of inventories to sales in year t-1. All continuous variables are standardized by subtracting the mean and dividing for the standard deviation. Standard errors reported in parentheses are clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	% Industry Sales		ROA (%)	
	Full sample	2019-2021	Full sample	2019-2021
	(1)	(2)	(3)	(4)
Star $\times$ Delivery Time	0.034***	0.041***	0.065***	0.065***
	(0.009)	(0.009)	(0.009)	(0.009)
Inventory $\times$ Delivery Time	0.002	0.003	-0.008	-0.005
	(0.002)	(0.002)	(0.008)	(0.009)
Inventory	-0.015***	-0.014***	-0.165***	-0.147***
	(0.004)	(0.005)	(0.014)	(0.015)
Star	0.705***	0.665***	0.339***	0.294***
	(0.025)	(0.024)	(0.018)	(0.018)
Industry-Country-Year FE	Yes	Yes	Yes	Yes
Obs.	61,464	24,889	56,644	22,954
Adj. R2	0.473	0.459	0.183	0.189