# Identifying macroeconomic shocks using firm-level data: Material shortages in the German manufacturing sector *

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**Abstract**

We propose a new identification strategy to quantify the effect of a supply chain shock on the real economy by combining sign restrictions on firm-level expectations and realizations with additional constraints on firm-level developments. We extract the exogenous share of material input constraints by contrasting the forecast performance of German manufacturing firms affected by material shortages with those firms facing no production impediments. Using a proxy VAR, we find that restrictive supply chain shocks lead to a significant and persistent increase in producer prices. Industrial production declines on impact, yet, this effect is statistically insignificant. Our methodology is not limited to our empirical application but might provide an avenue for the identification of shocks in other applications too.

**Keywords:** supply chain shocks, micro data, firm expectations, sign restrictions, producer prices

**JEL-Classification:** C32, C22, E31

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# 1. Introduction

Shock identification in in macroeconomic applications predominantly relies on sign and/or zero and/or narrative restrictions on the impulse responses. Alternatively, identification via external instruments also proves its value (Stock and Watson, 2012; Mertens and Ravn, 2013). However, finding and constructing such an instrument is not easy. We propose a novel identification strategy for construction such an instrument based on firm-level data. In our empirical application, we focus on the effect of a supply chain shock on the German manufacturing sector. More precisely, we construct an exogenous shock series that, arguably, is related to a supply chain shock on the German manufacturing sector by combining information on production impediments and production plans on the firm level. The procedure resembles imposing sign-restrictions on the micro level. Our results confirm the findings of existing studies on the effect of supply chain disruptions in Germany, e.g. Finck and Tillmann (2022)). We believe that our approach of identifying a macroeconomic shock can be applied in other settings too, provided the availability of suitable micro-data to properly discriminate between different types of shocks.

It is not only since the aftermath of the Covid pandemic that a growing body of literature works at better understanding and quantifying the effects of global supply chain shocks onto the economy. In this context, the German manufacturing sector provides a fruitful ground of given that Germany's manufacturing share in value added, amounts to 20.2 % in 2022, compared to the EU average share of 16.6% .[1] The success of Germany's manufacturing sector, which exported around 48% of its production in 2021, is however strongly dependant on imported intermediate goods and raw materials. Supply chains disruptions hence entail the risk of substantially affecting not only the sector itself but also the German economy as a whole.

The literature on supply chain linkages experienced a strong upswing since the outbreak of the Covid-pandemic, stressing the risk of micro-level shocks to propagate into global macro-level effects. Halts in individuals firms' production or the confinement of workers in ports created a series of supply chain disruptions that, e.g., have been shown to have driven up global import prices (Khalil and Weber (2022)). Our study is hence, by means of its empirical application, related to an extensive body of literature exploring the relationship between supply chain constraints, price setting, and inflation.

One strand of this literature focuses on constructing new supply constraint indices (e.g., Bai *et al.* (2024); Burriel *et al.* (2023); Benigno *et al.* (2022)), whereas other authors link to the literature on structural time series analysis and identification. They generally estimate the macroeconomic consequences of supply chain disruptions within a VAR framework using sign/and or and find a deteriorating effect of such shocks on output along with an increase in prices (e.g. Bai *et al.* (2024); Celasun *et al.* (2022); Finck and Tillmann (2022); Kilian

[1] https://www.destatis.de/Europa/DE/Thema/Industrie-Handel-Dienstleistungen/Industrie.html

*et al.* (2021)).
The set-identifying restrictions are occasionally augmented with direct restrictions on the values of the structural shocks such that they comply with the historical narrative about specific periods (e.g. Antolín-Díaz and Rubio-Ramírez (2018); Finck and Tillmann (2022)).

Methodologically, our work blends into the literature on identification using external instruments in VARs, as frequently used to identify monetary policy shocks (Miranda-Agrippino and Ricco, 2023; Stock and Watson, 2018; Gertler and Karadi, 2015) for identifying monetary policy shocks but also applied to global oil markets (Känzig, 2021).

The literature using micro data for macro identification is scarce, exemptions are e.g. Bachmann *et al.* (2013), who use firm level expectations to construct proxies for time-varying business uncertainty to estimate the impact of uncertainty on economic activity. Bachmann and Zorn (2020) use the responses of an investment survey among German manufacturing firms to identify aggregate demand and aggregate technology shocks. As outlined in detail below, the construction of our identification instrument involves evaluating firm level forecast errors. Even though different in research question and diverging in methodological aspects, other studies on the link between firm level expectation formations and macroeconomic shocks (Balleer and Noeller, 2023; Born *et al.*, 2022; Enders *et al.*, 2022).

The paper proceeds as follows: Section (2) provides details on the data, in particular the survey data for constructing our instrumental variable. Section (3) introduces our instrumental variable and lays out the estimation framework with the following sections (4) and (5) presenting results and robustness checks. Section (6) concludes.

## 2. Data

Our empirical application focuses on the effect of a supply chain shock on economic performance in the German manufacturing sector. With identification relying on firm level data from the ifo Business Survey (see below), we construct "pseudo" series for both industrial production and the producer price index to capture developments only in sectors represented in the firm level data. We do so by aggregating the manufacturing branches represented in the ifo survey weighted according to their share in value added [2]. As a measure of (endogenous) supply chain distortions, we use the share of firms indicating that their production is currently impeded by a lack of material, as published by the ifo Institute. Firms included in this measure are not restricted to only face material constraints, but may potentially also report other obstacles to production. Our identification strategy aims to extract from this series the share that is exogenous to other economic developments.

Popular measures of global supply chain disruptions include the Global Supply Chain Pressure Index (GSCPI, Benigno *et al.* (2022)) or the Average Port Congestion Index de-

[2] Our robustness checks show that results do not hinge on the inclusion of these pseudo series but still hold also when using the official industrial production and producer price index in the manufacturing sector.

veloped by Bai *et al.* (2024). Figure (1) shows that the ifo supply chain measures and the GSCPI generally exhibit a similar dynamic with a high degree of correlation (0.63). The share of German firms affected by material constraints is a natural candidate for measuring the degree to which firms in Germany are affected by supply constraints, potentially resulting from global supply chain disruptions. However, we also present results on alternative measures for supply chain stress.

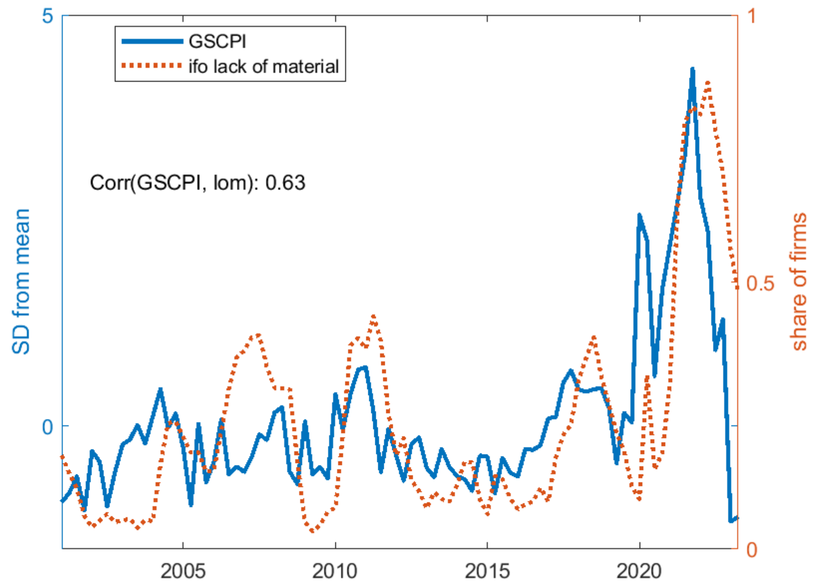



**Figure 1:** Measures of supply chain disruptions

*Notes:* The graph shows the evolution of the GSCPI and the share of firms reporting material constraints as production impediment. Both series show a high degree of correlation of about 0.63.

Our data spans the period between 2002Q1 and 2023Q2. The analysis is conducted at a quarterly basis as some of the data used for constructing the instrument is only available at this lower frequency. Production and prices are aggregated to quarterly measures by averaging across the monthly observations. In the following, we provide more details on the ifo survey in the manufacturing sector and relevant variables. We then outlines the identification strategy and the construction of the instrument.

**The ifo Business Survey in the Manufacturing Sector** We construct an external instrument based on firm level data from the ifo Business Survey in the Manufacturing Industry (from now on ifo survey), that has been conducted regularly since 1949. Participation is voluntary and firms do not receive any monetary compensation[3]. The respondent is usually a member of the company's senior management. Sauer and Wohlrabe (2019) document that 85% are indeed CEOs or department heads. The response rates for the ifo survey are typically high; approximately two-thirds of the firms initially contacted in mid-2021 participated

[3]The non-monetary compensation consists of receiving the sectoral and aggregate results of the survey.

in at least two survey rounds (Born *et al.*, 2022). High response rates persist also after the initial contact, maintaining an average monthly response rate of 82% (Enders *et al.*, 2022). The survey data is available at the firm level with firms being classified into the subsector level according to the ISIC Rev. 4 classification. The survey represents firms from all manufacturing sectors except the manufacturers of other transport equipment (C30) and the installation, maintenance and repair of machinery and equipment (C33). Table (1) provides an overview of the exact definition of manufacturing subsectors covered in our analysis. Note that survey data for the industries C10, C11 and C12 (manufacture of food, bevarages and tobacco) and for C13, C14 and C15 (manufacture of textiles, wearing apparel, leather and related products) is inquired as an aggregate.

| **ISIC Code** | **Subsector** |
|---|---|
| C10-C12 | Manufacture of food products, beverages and tobacco |
| C13-C15 | Manufacture of textiles, wearing apparel, leather and related products |
| C16 | Manufacture of wood and of products of wood and cork, except furniture |
| C17 | Manufacture of paper and paper products |
| C18 | Printing and reproduction of recorded media |
| C19 | Manufacture of coke and refined petroleum products |
| C20 | Manufacture of chemicals and chemical products |
| C21 | Manufacture of pharmaceuticals, medicinal chemical and botanical products |
| C22 | Manufacture of rubber and plastics products |
| C23 | Manufacture of other non-metallic mineral products |
| C24 | Manufacture of basic metals |
| C25 | Manufacture of fabricated metal products, except machinery and equipment |
| C26 | Manufacture of computer, electronic and optical products |
| C27 | Manufacture of electrical equipment |
| C28 | Manufacture of machinery and equipment n.e.c. |
| C29 | Manufacture of motor vehicles, trailers and semi-trailers |
| C31-C32 | Manufacture of furniture, other manufacturing |

**Table 1:** Subsectors of the Manufacturing sector (C)

*Notes:* The table lists the manufacturing subsectors covered in the ifo Business survey, following the ISIC Rev. 4 sector classification.

Each month, between 2000 and 5000 manufacturing firms participate in the ifo survey, responding to a broad range of mostly qualitative questions on developments within their sector. Many of the questions are asked at a monthly frequency, while others are asked only once per quarter. Our focus is on questions eliciting information about firms' price and production expectations, their actual realizations, potential production impediments, and firm-level demand developments.

**ifo survey data relevant for our identification** At the heart of our identification strategy is firm level information on potential production impediments, in particular material shortages. At the beginning of each quarter, firms are queried about potential production obstacles, which may include financial constraints, demand or labor shortages, or the unavailability of materials. Concretely, this question reads

> *"Our domestic production is currently constrained by...*
> - *too few orders*
> - ***lack of raw material or pre-materials***
> - *insufficient technical capacity*
> - *lack of skilled employees*
> - *lack of low-skilled employees*
> - *difficulties of financing*
> - *other."*

Not answering this question is – similar to answering that production is currently *not* impeded – interpreted as not being affected by any adverse development. Balleer and Noeller (2023) study this question in more detail and document that the share of firms reporting material shortages tends to be pro-cyclical. They stress the importance of within industry variation in responses to this question as opposed to between industry variation and further note that material constraints are not very persistent at the firm level.

The ifo survey provides an additional large set of firm characteristics, among other, firms provide each month qualitative information about price and production expectations and realisations as well as on their demand situation. While the qualitative nature of the questions complicates quantitative statements, it reduces measurement errors. Figure **??** visualises the timing of those question relevant for our analysis.

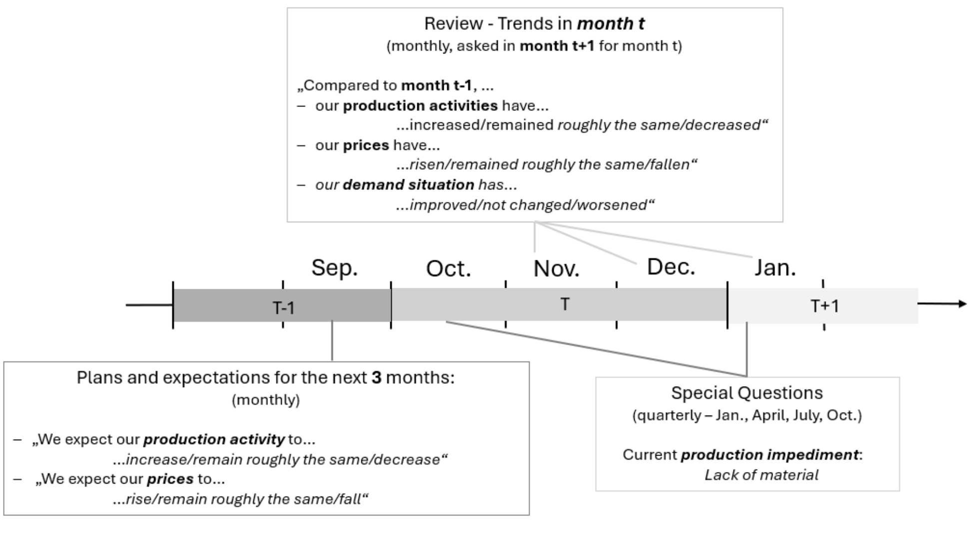



**Figure 2:** Timing of relevant survey questions

*Notes:* The graph visualises the timing of different questions in the ifo survey we exploit in our identification strategy.

It is important to note the time horizons under consideration for each of the questions: While expectations are elicited with respect to the upcoming two to three months, realizations are stated for the preceding month compared to the month before. Information on production impediments is only requested once at the beginning of a quarter. We align information from monthly questions to comply with the quarterly nature of the production impediment question by aggregating answers accordingly. Section (3) provides more details.

## 2.1. What dampens industrial production?

Before turning to the main analysis, we briefly present a few additional stylised facts on self-reported production impediments. This does not only gives insights into the production climate of firms over time but also motivates the construction of our instrument.

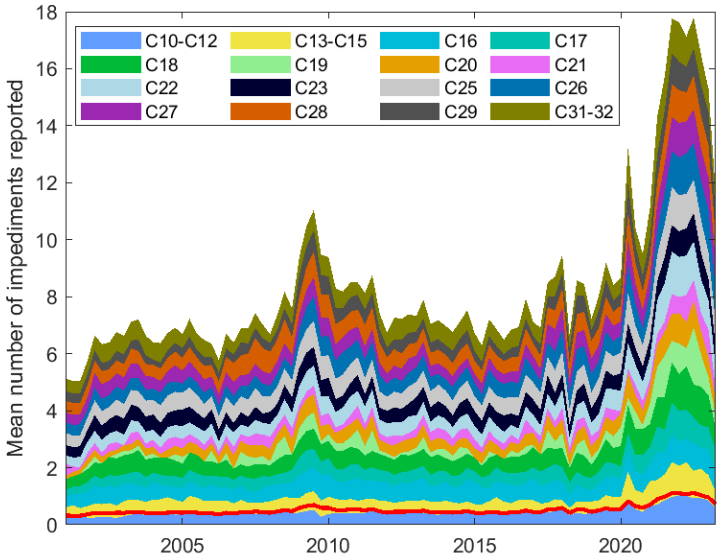



**Figure 3:** Average number of reported impediments

*Notes:* The graph visualises the average number of impediments reported by each firm within a sector over time. The red line shows the average number of impediments across all firms in the sample.

Figure (3) shows the average number of impediments reported by firms across sectors and time. On average, a firm reports 0.52 impediments per quarter. Interestingly, this number is quite stable across sectors and time. Major events, e.g. the Great Recession, the Global Financial Crises or more recently the outbreak and the aftermath of the Covid pandemic seem to affect firm responses, in terms of numbers of reported impediments, across sectors in a rather uniform way.

Delving deeper into underlying production impediments, figure (4) and (5) show the share of firms stating to be exclusively affected by one of the possible production impediments over time, separately for all manufacturing sectors [4]. This visualization offers three main

[4] As before, the question also presents as possible impediment "lack of low-skilled employees". This answer, however, was only introduced in 2020, hence we decided decided to abstract from it in the following.

insights. First, it reveals the periods during which firms were most affected by a specific production constraint. Second, it identifies the sectors that were most affected by a certain production impediment. Third, it indicates whether certain obstacles tend to occur around similar times, although not necessarily affecting the same firms.

We group impediments into three broader groups: Financial, demand, and production-side related constraints. Financial constraints appear to be predominantly important for firms involved in the publishing, printing, and media industry, as well as for those working with cokery, mineral oil, fissile, and fertile materials. In comparison to other impediments, the share of firms solely affected by financial constraints, however, is quite low, with some spikes around the Great Recession and the sovereign debt crises. Historically, a significant proportion of firms have reported experiencing order shortages, particularly those in the chemical industry and the automotive sector. With a few exceptions during the Great Recession, the Global Financial Crisis and the early onset of the Covid-19 pandemic, the proportion of firms (exclusively) reporting demand shortages has been relatively high, averaging at around 50%. Concurrently, there has been a gradual build-up in the shortage of skilled workers since 2010 across all sectors. A few firms report insufficient production capacity as their sole reason for low production. However, since 2010, this tends to co-move with the share of firms (uniquely) reporting order shortages. Figure (5) provides more details on the answer to material impediments which is at the heart of our identification strategy. We show the share of firms uniquely affected by material constraints along with information on major events that, in their aftermath, eventually triggered disruptions to global supply chains. Two observations stand out. First, the majority of sectors reporting material constraints at any point in time are sectors where production relies heavily on intermediate materials or capital goods, such as e.g. the vehicle- (C29) or machinery- sector (C28). Second, peaks in this series correspond well with (global) disruptive events. For instance, we observe a high share of firms in the vehicle manufacturing sector reporting material lacks around the major earthquakes in Japan in 2011 and 2016. We further observe a rapid increase in firms reporting material shortages following the disruptions arising due to the pandemic or the blockade of the Suez canal. With regard to the crucial answer for our work, the share of firms reporting material shortages, we observe that in more recent years, this question tends to negatively co-move with the question on orders. However, by construction, we do not observe the same firm in both answers within the same quarter. This observation warrants some discussion on the relevance of demand effects when introducing the external instrument below.

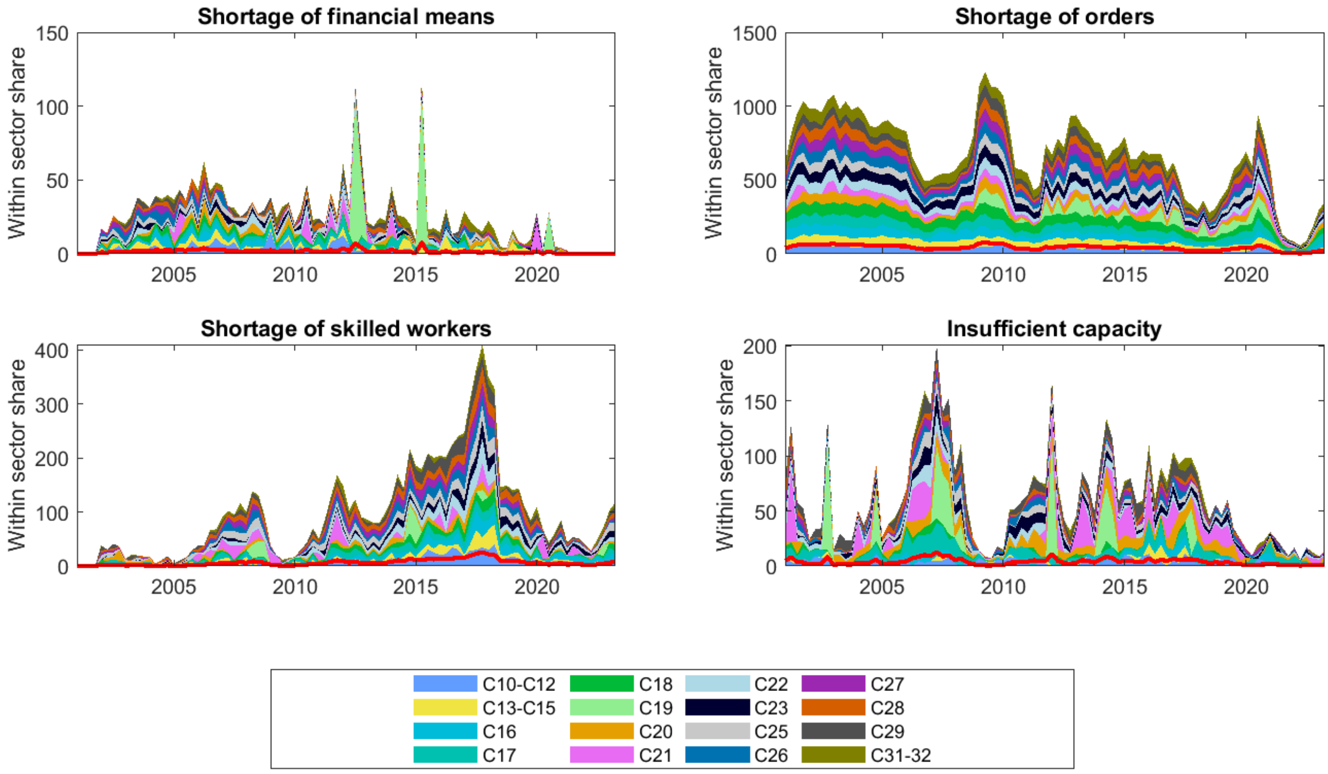



**Figure 4:** Share of firms reporting different unique impediments

*Notes:* The figure shows the accumulated within sector shares of firms reporting the respective impediment. The red line denotes the mean share over all sectors that reports the specific impediment.

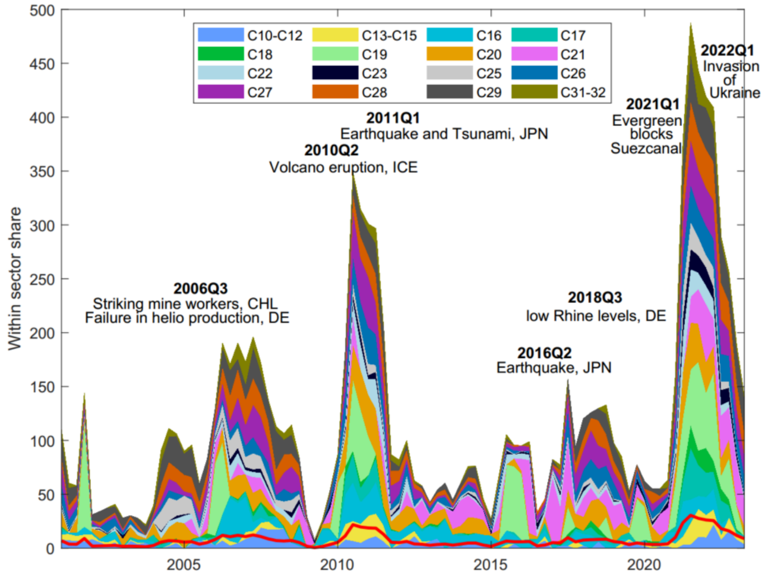



**Figure 5:** Share of firms reporting a lack of material as unique impediment

*Notes:* The figure show the accumulated within sector shares of firms reporting a lack of material. The red line denotes the mean share over all sectors that reports the specific impediment.

# 3. Methodology

## 3.1. Identification based on firm level data

Identification in VAR applications is regularly achieved via Cholesky ordering, sign restrictions, narrative restrictions, long run restrictions or instrumental variable (proxy VAR) approaches. Our work adds to the latter by showing that firm level provides useful information for identifying a macroeconomic shock. Our empirical application focuses on the effect of an unexpected material input bottleneck on the German manufacturing sector.

**The firm level data based instrument** Our identification strategy is based on a comparison of firm level forecast errors with respect to price and production developments across two groups of firms: those who report experiencing material input shortages as opposed to those not affected by any production impediment. Therefore, we impose sign restrictions on forecast errors at the firm level that are in line with the general notion of a supply shock. Coupled with additional information on obstacles to production and demand developments, we proceed to identify firms that have been unexpectedly hit by a material input supply shock, i.e. their forecast error should be due to a material input supply shock.

We start by defining the firm level forecast error, similar to Born *et al.* (2022) and Bachmann *et al.* (2013). Remember that expectations on production and price developments for the upcoming three months of firm $i$, $E^i_{T-1}\{x^i_T\}$[5], are elicited once a month. Throughout the text, $T$ refers to quarterly measures, whereas $t$ denotes monthly variables. $x^i$ denotes qualitative firm level information on either price or production developments. For our baseline instrument, firms' responses in the last month $t$ of quarter $T-1$ hence indicate their expected production (price) development for quarter $T$. Every month, firms further indicate realized production and price developments for the previous month. While the questions on expected developments provide a natural candidate response to align with the quarterly frequency of the other data, we need to aggregate month by month information on actual realisations to the quarterly frequency. We start by recoding monthly realisations $x^i_t$ such that $x^i_t \in \{-1, 0, 1\}$, depending on whether production (prices) *declined, did not change,* or *increased.* And proceed by taking the sum of the three monthly values over the corresponding quarter: $x^i_T = \sum_{k=0}^{2} x^i_{t+k}$. We interpret a positive value of $x^i_T$ as an increase, a negative one as an overall decrease, and 0 as no change in prices (production) during that quarter. We recognize the shortcoming of this aggregation in that it does not allow to account for the magnitude of changes. Hence, a sequence consisting of no change followed by an increase and ultimately a decrease would amount to unchanged production (price) over the quarter

[5] As they are asked every month for the upcoming three months, to underline their monthly nature, it would be more appropriate to denote the expectations as $E^i_t\{x^i_{t+3,t}\}$. As we however only rely on the expectation given in the last quarter of a month and hence referring to the upcoming quarter, we use the quarterly notation.

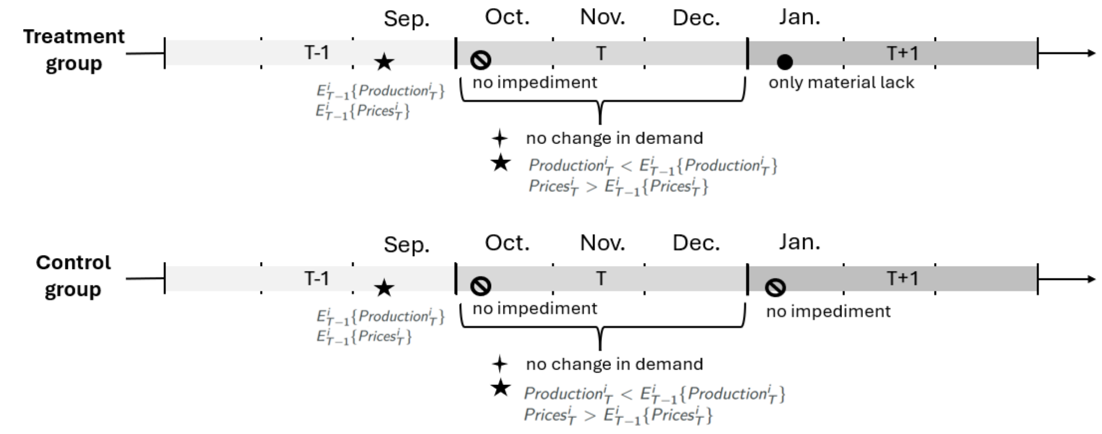
— although the decrease might quantitatively exceed the previous increase. We proceed to flag firm level forecast errors as follow

$$x_T^i - E_{T-1}^i\{x_T^i\} = \begin{cases} 0 & \text{if signs of } x_T^i, E_{T-1}^i\{x_T^i\} \text{ coincide} \\ 1 & \text{else} \qquad \forall x, i. \end{cases} \tag{1}$$

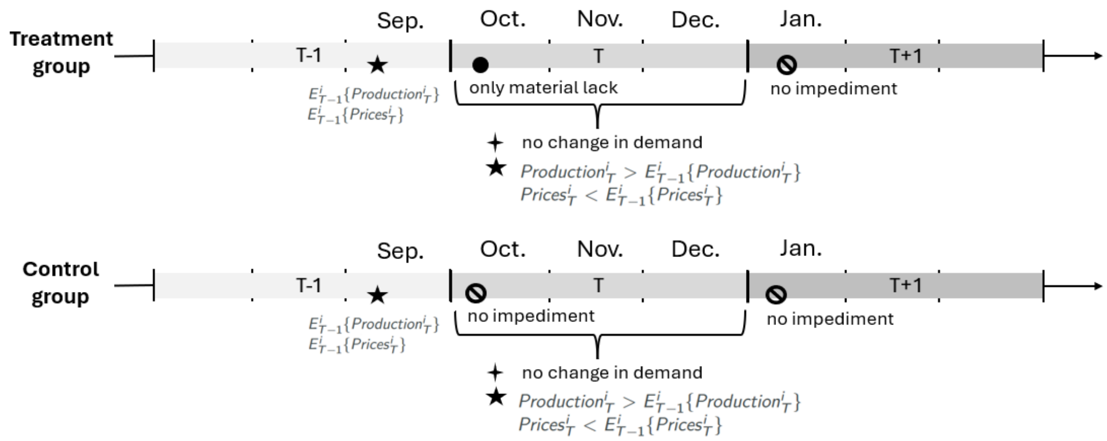
Equation (1) implies that a forecast error occurs whenever firms were either too optimistic or too pessimistic in their expectations on prices (production).

To identify an unexpected material shortage at the firm level, we compare the forecasting performance across firms that differ in terms of their reported production impediment(s). In this setting, "unexpected" refers to material lacks that are not yet a concern at the time when firms state their production (price) expectations for the upcoming quarter but emerge only after responding. We suspect that firms reporting a material constraint at the beginning of a quarter have (to a large extent) already been constrained during the past month(s) — the extent to which a sudden material impediment arises coincidentally exactly at the time of answering to the survey should be rather small. In turn, apart from material shortages due to supply chain shocks or other physical obstacles to receiving material, an unexpected increase in demand may also trigger firms to report material constraints as their material orders were simply too low to keep up with demand. Firms provide monthly information on their demand situation. We therefore construct an auxiliary quarterly variable on demand developments, similar in construction to the quarterly measure on production and price developments.

Based on these variables, we construct our instrument. Therefore, we flag a firm in our sample as being hit by a restrictive material input shock if i) price and production expectations for quarter $T$ are better than actual realisations, ii) in quarter $T$, the firm does not indicate any production impediments but reports material shortage as the unique production impediment in quarter $T+1$, and iii) the firm does not report a change to demand during quarter $T$. Note that in the context of prices, expectations are "better" than realisations if expected prices were lower than realised prices, whereas in the context of production, expectations were "too optimistic" if realised production falls short off expected production developments. Concurrently, there may be a number of firms that are (unexpectedly) hit by a loosening material shock, i.e. firms faced material constraints that resolved during the quarter. We adopt a similar approach as before and flag a firm as hit by a loosening material constraint shock if i) price and production expectations for quarter $T$ are worse than actual realisations, ii) in quarter $T$, the firm indicates that production is (uniquely) constrained by material shortages but in the consecutive response, no production impediment is reported, and iii) the firm does not report a change to demand during quarter $T$. By imposing con-




**(a)** Timing and constraints for identification of a restrictive shock




**(b)** Timing and constraints for identification of a loosening shock

**Figure 6:** Timing of survey answers and firm level constraints for identification of a material supply supply chain shock

*Notes:* Panel (a) and (b) visualise the conditions imposed on firms to be flagged as being hit by an unexpected restrictive (panel (a)) or loosening (panel (b)) material input supply shock for our benchmark instrument.

straints on two consecutive answers in condition (ii), we hope to capture anticipation effects regarding production (price) expectations to the best possible extent.

To construct the final shock series for identification of a restrictive material supply shock[6], we proceed in four steps, including the definition of treatment and control groups. Figure (6) visualises our identification assumption for both groups of firms.

*Step 1:* Among the firms satisfying our conditions on material impediments and demand developments for a restrictive material input shock (treatment group figure (6a)), we calculate for each manufacturing industry the share of firms committing a negative forecast error ($E^i_{T-1}\{x^i_T\} > x^i_T$ for production, $E^i_{T-1}\{x^i_T\} < x^i_T$ for prices). We weight individual firms with the firms' headcount to acknowledge that firm size may matter for the spread of bottlenecks. We call this group treatment group R. Second, we define treatment group

[6]Since our proposed estimation set up is linear, the effect of a loosening material input shock is simply the reverse of the results shown here

L as the share of firms reporting realisations better than expectations ($E^i_{T-1}\{x^i_T\} < x^i_T$ for production, $E^i_{T-1}\{x^i_T\} > x^i_T$ for prices) based on firms satisfying the conditions on material and demand pertaining to a loosening input supply shock (treatment group figure (6b)). We proceed by defining for both treatment groups an associated control group. Firms in both control groups indicate neither in quarter $T$ nor in $T+1$ any production constraints (in addition to an unchanged demand). To define the exact control groups, we then calculate the share of firms (at the sector level) either facing worse (control group R) or better (control group L) realisations than expected. Again, figures (6a) and (6b) illustrate the restrictions on treatment group R and control group R.

*Step 2:* We take the the difference between the share of firms facing a restrictive material input supply shock (treatment group R) and those confronted with a loosening material supply shock (treatment group L) (see minuend on the RHS of Equation (2)).

*Step 3:* For firms not reporting any impediment(s), we calculate again the difference between the share of firms experiencing worse realisations than expectations (control group R) and the share of firms encountering better realisations than expected (control group L) (subtrahend on the RHS of Equation (2)).

*Step 4:* We construct the sector level exogenous shock series, $iv_t$, as the net difference between treatment R and control R and treatment L and control L groups. In a final step, we aggregate the sector level series to an aggregate manufacturing series by summing them up using their share in gross value added of total manufacturing as weight (see equations (2) & (3)).

$$iv_t = \left[sh^R_{t,mat|\bar{d}} - sh^L_{t,mat|\bar{d}}\right] - \left[sh^R_{t,noimp|\bar{d}} - sh^L_{t,noimp|\bar{d}}\right], \tag{2}$$

where

$$sh^i_{T,j|\bar{d}} = \sum_{s=1}^{N} sh^i_{T,j,s|\bar{d}} \frac{BWS_{Y,s}}{BWS_Y} \quad \forall j \in (mat, noimp),\ i \in (R, L), \tag{3}$$

and

$$sh^i_{t,j,s|\bar{d}} = \frac{weighted\ \#firms\ sign\ \&\ impediment\ (j)\ satisfied}{weighted\ \#firms\ impediment(j)\ satisfied}. \tag{4}$$

$Y$ denotes a year, $R$ and $L$ refer to restrictive or tightening shocks, i.e. expectations better or worse than realisation, respectively. *mat* indicates a material input constraint according to our conditions above and *noimp* refers to firms without any constraints. $|\ \bar{d}$ indicates that we only consider firms where demand remains unchanged during the quarter. $BWS_{Y,s}$ is gross value added of sector $s$ in year $Y$ of quarter $T$, and $BWS_Y$ is total gross value added in the manufacturing sector.

## 3.2. Discussion of the external instrument

The objective of constructing the proxy variable is to identify the extent to which supply chain impediments influence production and price developments. Our approach intends to retrieve the share of firms exogenously hit by an input shock. To serve as a valid instrument, our shock series needs to comply with the well established relevance and exogeneity conditions. We provide some statistics on the relevance of the instrument from a statistical perspective below. In the following, we provide some more intuition on our instrument.

A material or supply chain shock is, in nature, similar to any other supply shock in a sense that it most likely adversely affects prices and production, hence the sign restrictions on the forecast error. Yet, this does not uniquely identify *the* shock that we are after, wherefore we impose additional constraints based on reported production impediments to identify those firms where we can trace forecast errors back to sudden material input constraints. Thereby, our approach extracts the share of firms where we believe that their forecast error is, to a large extent, driven by an unexpected material input constraint. Importantly, we remove those firms that might have anticipated this bottleneck, i.e. in anticipation of such a bottleneck, their expectations already adjusted. The definition of control groups addresses two concerns related to the exogeneity of the instrument. First, it is likely that not all firms can always get their expectations about price and production developments right. Second, numerous alternative shocks may cause firms' expectations to differ from realizations. These may be shocks that are difficult to control for at the firm level since they affect sectors as a whole. These may be, for instance, fiscal- or monetary policy interventions or other idiosyncratic shocks that could invalidate identification. In order to remove their influence from the shock series, we employ the two control groups. This relies on the assumption that these shocks affect all firms equally and implies that the response of firms hit by a material shock to a possibly joint occurrence of other shocks does not structurally differ from the response of firms not reporting any material constraints. Furthermore, we address concerns regarding the endogenous build-up of material shortages due to an increase in demand by conditioning firms not to face changes in their demand situation. Our approach identifies an unexpected supply chain or material input shock at the firm level. However, we are unable to discriminate between first, second, or higher-round effects that may eventually arise due to the interconnection between firms. Additionally, we clarify that a firm cannot experience an input supply shock in two consecutive quarters by construction.

Yet, we believe that not being able to account for endogenous network effects does not pose a major concern for our identification strategy. What is important for identification is that firms did not expect that they face constraints with respect to resources required for production. However, it does not matter whether such an unexpected situation arises as a consequence of a purely exogenous event, e.g. a natural disaster, or is the result of an endogenous built-up of resource constraints across firms. That is, a firm may face unexpected material shortages not because it is directly affected by a natural disaster but at least one of its supplier firms is. Yet, our application quantifies the macroeconomic effect of a material or supply chain bottleneck on the economy. Hence, what is important for us is to understand the extent with which firms are hit by such a shock and not to perfectly discriminate who was hit first or might have propagated the shock at the firm level. The crucial constraint is that a firm did not expect being hit by such a shock such that we can exploit the variation in the share of firms unexpectedly hit for our causal analysis.

For further intuition, note that whenever our exogenous shock series (2) is greater than 0, this is equivalent to

$$sh^R_{t,mat|\bar{d}} - sh^R_{t,noimp|\bar{d}} > sh^L_{t,mat|\bar{d}} - sh^L_{t,noimp|\bar{d}}, \tag{5}$$

implying that in case of a restrictive material supply shock, after accounting for potential distortions from other idiosyncratic shocks and a general mismatch in expectations and realisations, the share of firms negatively affected by a material input supply constraint exceeds those potentially experiencing an unexpected loosening of material input impediments.

Table (A1) provides the average number of firms observed in each of the four groups identified for constructing the proxy.

## 3.3. Estimation

We estimate a three variable Bayesian proxy VAR, similiar to Stock and Watson (2012) and Mertens and Ravn (2013). Our estimation set up is also akin to the procedure in Miranda-Agrippino and Ricco (2017). In our baseline specification, production and prices are entered into the model in log differences. As an endogenous measure of supply chain pressure or input material shortages, we include the share of firms indicating "lack of material" in the ifo Business Survey as a reason for production impediments. It should be noted that this share includes any firms reporting this impediment, without any restriction on any other variable.

The response of production and prices to a shock to global supply chains is identified based on an instrument designed to extract the purely exogenous part of this variable. The crucial assumption underlying this identification procedure is the relevance and exogeneity of the instrument. While we have already argued for the relevance and exogeneity of the instrument above, from this framework it becomes clear that we can only recover the response to a supply chain shock if the instrument is solely correlated to the shock of interest and unrelated to any other shock in the system.

Starting point for our analysis is a regular reduced-form VAR(p) model given by

$$\mathbf{y}_t = \mathbf{c} + \sum_{i=1}^{p} \mathbf{B}_p \mathbf{y}_{t-i} + \mathbf{u}_t, \tag{6}$$

where p denotes the lag length, $\mathbf{c}$ is an $n \times 1$ vector of constants, $\mathbf{y}_t$ is an $n \times 1$ vector of endogenous variables and $\mathbf{u}_t$ is the $n \times 1$ vector of reduced-form innovations. As usual, we assume that the reduced-form errors are linearly related to the structural errors such that

$$\mathbf{u}_t = \mathbf{\Phi} \nu_t, \tag{7}$$

where $\mathbf{\Phi}$ denotes the impact matrix and $\nu_t$ is an $n \times 1$ vector containing the structural shocks we are after. By definition, the structural shocks are mutually uncorrelated, i.e. $Var(\nu_t) = \Omega$ is diagonal and $Var(\mathbf{u}_t) = \mathbf{\Sigma} = \mathbf{\Phi \Omega \Phi}'$.

**Identification via external instrument** To recover the impact of a supply chain shock, we use the newly introduced instrument as a proxy for the structural supply chain shock. We denote the instrument with $x_t$. Formally, for the instrument to be valid it needs to be correlated with the shock of interest (relevance condition (8)) but uncorrelated to all other shocks (exogeneity condition (9))

$$\mathbb{E}[x_t \nu_{1,t}] \neq 0 \tag{8}$$

$$\mathbb{E}[x_t \nu'_{-1,t}] = \mathbf{0}, \tag{9}$$

where $\nu_{1,t}$ denotes the (structural) supply chain shock and $\nu_{-1,t}$ collects all other shocks. To identify the structural shock and given these two assumptions hold we can write

$$\mathbb{E}[x_t \mathbf{u}'_t] = \Phi \mathbb{E}[x_t \nu'_{\mathbf{t}}] = (\phi_{\mathbf{1}} \quad \mathbf{\Phi}_{-\mathbf{1}}) \begin{pmatrix} \mathbb{E}[x_t \nu_{1,t}] \\ \mathbb{E}[x_t \nu'_{-1,t}] \end{pmatrix} = \phi_1 \alpha, \tag{10}$$

stating that $\phi_1$ is identified up to scale. Further

$$\mathbb{E}[x_t \mathbf{u}'_t] = \begin{pmatrix} \mathbb{E}[x_t u_{1,t}] \\ \mathbb{E}[x_t \mathbf{u}'_{-1,t}] \end{pmatrix} = \begin{pmatrix} s_{1,1}\alpha \\ \mathbf{s}_{1,1}\alpha \end{pmatrix}, \tag{11}$$

such that

$$\frac{\mathbf{s}_{-1,1}}{s_{1,1}} = \frac{\mathbb{E}[x_t \mathbf{u'}_{-1,t}]}{\mathbb{E}[x_t u_{1,t}]}, \tag{12}$$

given that $\mathbb{E}[x_t u_{1,t}] \neq 0$. Intuitively, equation (11) resembles the well known IV estimator and serves as departure for two stage regression procedure, where $u_1$ is first regressed onto the instrument $x$ and in a second step, $\mathbf{u}_2$ is regressed upon the fitted values $\hat{u}_1$, that reflect the exogenous part of the reduced form innovation explained by the proxy. Our implementation for estimation is akin to Miranda-Agrippino and Ricco (2017).

To estimate the reduced form VAR, we use a Minnesota prior on the parameters and two lags, as suggested by the Akaike-Information criterion, in our baseline specification. Production and prices enter our model in log differences.

# 4. Results

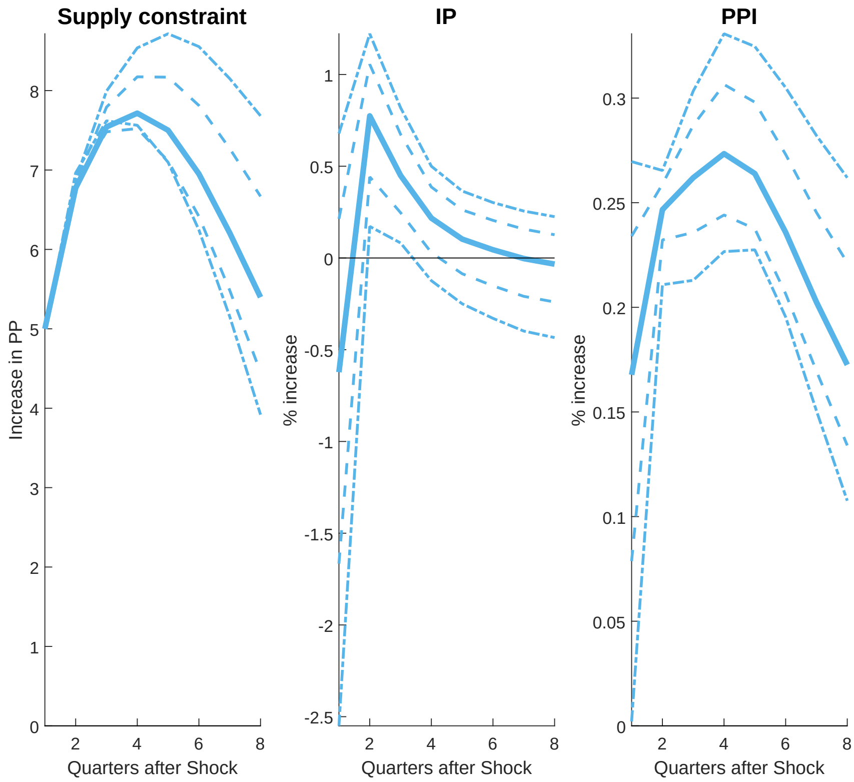
Prior to quantifying the impact of a supply chain shock on the economy, it is necessary to assess the strength of our newly constructed external instrument. While we previously argued for its exogeneity, we now test for the relevance of the IV, i.e. the strength with which it is correlated to the shock of interest. We follow Montiel Olea *et al.* (2021) and calculate the F-statistic from regressing the residual of the supply chain measure (ifo survey on material constraints) constructed from the first stage of the VAR onto our instrument. According to them, a relevant instrument should exhibit a corresponding F-statistic of at least 10. Table (2) shows the results. We also present the F-statistic for a battery of robustness analyses that we present further below. The strength of the instrument varies slightly across the exact specifications of the VAR, yet for our baseline, the results suggest that the instrument should perform satisfactorily from a purely statistical point of view. It is noteworthy that the IV performs worst for a naive re-specification of the instrument (more below), which reassures that accounting for a variety of potential confounding factors is warranted. Notwithstanding its derivation from micro-firm-level data, the instrument exhibits a robust performance when employed in conjunction with an alternative measure of supply chain disruptions, namely the GSCPI from the Federal Reserve Bank of New York.

| **Specification** | F-stat | F-stat (robust) |
|---|---|---|
| **Baseline** | 68.53 | 16.36 |
| **Sensitivity analysis: IV specification** | | |
| Naive IV | 22.34 | 12.14 |
| Alternative timing expect. | 50.76 | 11 |
| Lax price & production | 7.43 | 6.4 |
| **Sensitivity analysis: Model specification** | | |
| No Covid | 78.68 | 39.75 |
| Lag length (3) | 58.99 | 16.66 |
| Alt. Prior | 68.52 | 16.36 |
| OLS | 68.59 | 16.43 |
| GSCPI | 68.91 | 63.56 |

**Table 2:** F-statistics for IVs

*Notes:* The table shows the F-statistics from the regression of the endogenous supply chain measure onto the instrument. The instrument is constructed as explained to remove the endogenous share of firms reporting lack of material. The naive instrument is constructed as the share of firms *solely* reporting material constraints as obstacles to production. The IV based on alternative timing, conditions on price and production expectations in the first month of each quarter, whereas the instrument with lax price and production condition only requires either production or price realisations to differ from their expected developments. The table also shows F-statistics for specifications detailed in the robustness section. Following Montiel Olea *et al.* (2021) any F-statistic greater 10 is indicative of a relevant instrument. The robust statistic accounts for heteroskedasticity.

The remainder of this section quantifies and discusses the effects of an unanticipated supply chain shock onto the real economy in Germany. Figure (7) plots the baseline impulse responses. All results are normalized to represent the response to an increase in the share of firms reporting material lack as an impediment (potentially in conjunction with other obstacles) by five basis points. Since industrial production and the producer price index are expressed in log differences, we present responses as percentage changes across quarters. A sudden material input shortage leads to an immediate increase in the relative number of firms reporting material shortages, with the share of affected firms remaining elevated for the following quarters. The responses of our two macroeconomic variables are particularly noteworthy. An unexpected shortage of material does not affect production significantly, whereas it does cause a surge in producer prices. Although industrial production initially declines, it quickly rebounds, yet this this adjustment is only marginally statistically significant. Prices, on the other hand, react more strongly and persistently. On impact, producer prices rise by approximately 0.17%. The effect reaches its peak after three quarters, with a quarter-over-quarter increase exceeding 0.27%. Subsequently, price increases decelerate, yet these effects remain statistically significant throughout the horizon considered in our analysis.




*Notes:* Impulse responses to an identified supply chain shock, normalised to an five basis point increase in the balance of firms affected by a material shortage. Identification based on the IV presented in the main text. Dashed areas show 64% and dashed dotted area 90% confidence bands. The supply constraint corresponds to the share of firms reporting material lack as production impediment.

**Figure 7:** Impulse responses to a supply chain shock

Next, we investigate the historical contribution of material input supply shocks to our variables over the last two decades (figure (8)). In the period following the onset of the Covid-19 pandemic and the subsequent implementation of anti-contagion measures, there has been a growing interest in the potential impact of shipping delays or material shortages on business cycle activity. To better understand the importance of supply chain shocks in shaping economic activity, we perform a historical decomposition of industrial production and producer prices. Two key observations stand out. First, the pattern of how material constraints drive industrial production is highly volatile. Second, the impact of material constraint shocks on prices is characterized by alternating periods of upward and downward pressure. Prior to 2007, material shortages exerted downward pressure on prices. With the rebound from the Great Recession, material shortages contributed to the increase in prices for a few quarters. Subsequently, it is only since 2018/2019 that, in accordance with the prevailing narrative of global supply chain constraints and material shortages, material supply shocks have contributed significantly to the observed increases in producer prices. Furthermore, the shock has had a predominantly negative impact on the share of firms reporting material shortages as a production impediment until approximately 2020. Since that time, however, the impact of restrictive material supply shocks on the increase in firms reporting material constraints has been positive.

Our findings align with recent observations. Despite a rise in reports of material shortages, industrial production remained relatively stable during this period. However, prices exhibited a notable acceleration.

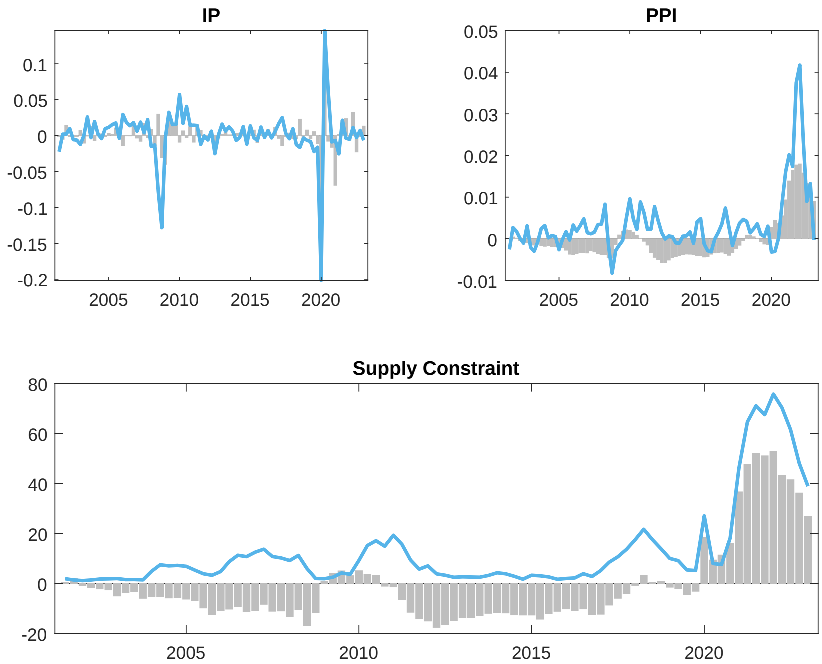



**Figure 8:** Historical Contribution of supply chain shocks

*Notes:* Historical Contribution Industrial production and producer prices in log differences. Identification based on the IV presented in the main text. The supply constraint corresponds to the share of firms reporting material lack as production impediment.

# 5. Sensitivity analysis

In order to ensure the robustness of our results, we have implemented a series of checks designed to verify that they are not dependent on specific assumptions. These checks have been grouped into two categories: firstly, sensitivity checks on the instrument, with particular attention paid to the timing assumptions on the underlying question; and secondly, an assessment of the sensitivity of our results to changes in the specification of the overall model.

**Alternative timing in firm responses** The construction of the instrument is based on firm level constraints configured to extract the exogenous part of input supply constraints. Since our shock series depends on conditions retrieved from survey data including questions with an only vaguely formulated time horizon, we address two alternative timing assumptions. Since the question on expectations about future price and production developments refers to the horizon "within the next two to three months", it leaves the exact horizon under consideration open for interpretation. We hence adjust our conditions on both the loosening and restrictive material input shock to take answers on the expectations questions from the first month of the quarter as opposed to answers from the last month of the previous quarter. Second, our firm level sign restrictions require that production and price expectations are worse (better) than actual realisations. We experiment with an alternative versions where either price or production or both expectations can have performed worse (better). Furthermore, we contrast our baseline results with a naive approach that employs a variant of our instrument, which simply states the share of firms exclusively reporting material impediments as obstacles to production. This naive instrument only accounts for the share of firms solely affected by the lack of material during a quarter. Figure (9) presents the impulse response functions where identification is based on these alternative instrument definitions.

The naive instrument indicates that the instantaneous effect on prices is more pronounced, yet also declines more quickly over the horizon under consideration. This observation is interpreted as suggestive evidence that explicitly accounting for confounding effects due to demand adjustments is warranted. Additionally, it is noted that statistically speaking, the naive instrument performs slightly worse than our proposed IV in terms of relevance (table (2)). Turning to the instrument with a slight adaption in the timing assumption of expectations, the F-statistics on the relevance condition slightly decrease, yet the effect on prices and production is hardly affected. Consequently, when the instrument is only required to differ from its expected realisation in terms of prices or production (or eventually both), it fails the test for relevance from a statistical perspective. We interpret this finding as evidence that, in fact, what is needed is a clear-cut "sign-restriction" at the firm level to satisfactorily extract the structural shock.

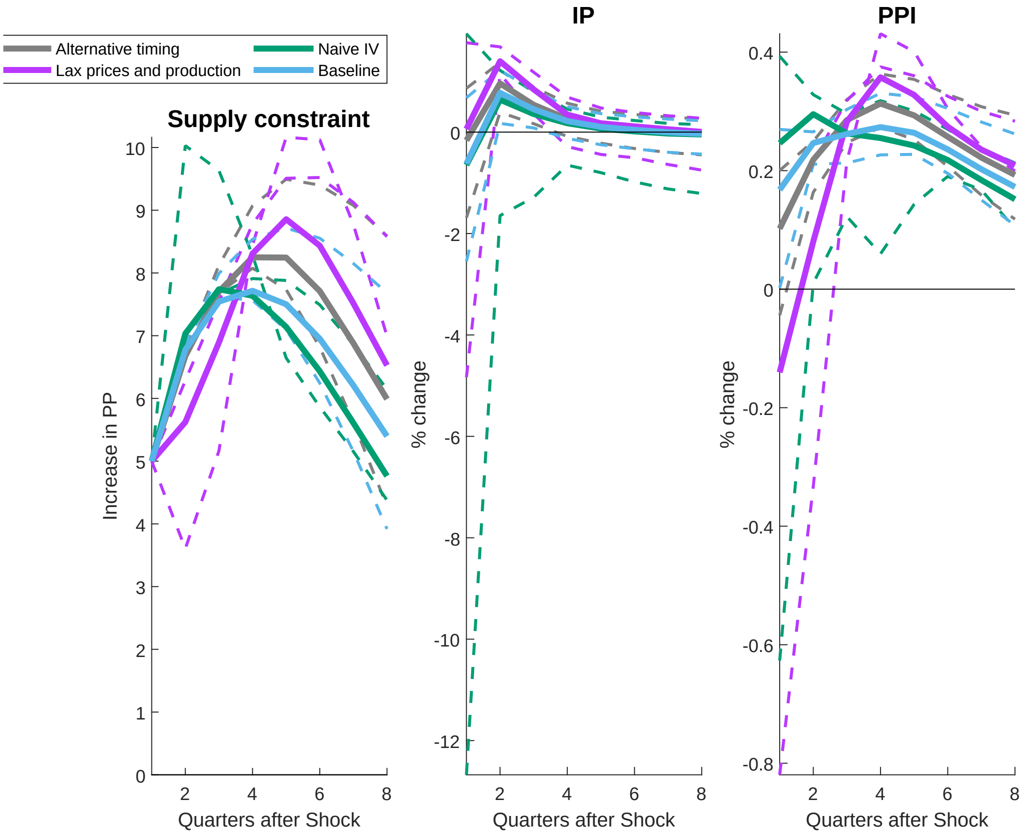



**Figure 9:** Impulse responses to a supply chain shock

*Notes:* The graph shows the impulse responses of the supply constraint measure, prices and production to a five basis point increase in the balance of firms reporting material constraints. Identification is based on variants of the baseline IV presented in the main text. Dashed areas show 90% confidence bands. The supply constraint corresponds to the share of firms reporting material lack as production impediment.

**Model specifications** The model is re-estimated with the following modifications: First, three lags are included in the model. Second, an uninformative Jeffrey prior is used on the parameters, with the results presented along with those based on an OLS regression. Third, the data is limited to 2020 Q1 to account for the potential effects driven by the unprecedented supply chain constraints during the Covid pandemic.Lastly, we use the GSCPI as endogenous supply chain measure in our VAR.

Figure (10) shows the results of these robustness checks. Note that we again standardize all results to represent the effect of an increase in the balance of firms experiencing a material shortage by five percentage points. This holds true for all specifications except the one including the GSCPI index, where results are instead standardised to an increase in the index by one unit, i.e. one standard deviation of the underlying series.

The alternative model specifications do not significantly alter our key results. While the effects on industrial production are largely consistent across all specifications, we observe some marginal differences in the response of prices. First, although our proposed external instrument is similarly effective in extracting the exogenous component of the GSCPI index, (table (2), it is worth noting that the resulting build up in prices is slightly greater than in all other specifications. Similarly, the impact on production is also somewhat more pronounced. This may be due to the difficulty in reconciling the magnitude of the two endogenous series measuring supply constraints. However, the results indicate similar trends, and the qualitative differences are nonetheless small. The external instrument performs well in extracting the relevant exogenous share of the endogenous supply chain measure that is not constructed from a similar data source as itself and hence not reliant on firm responses, as indicated by the F-statistics (table (2)). Furthermore, it can be observed that the effect on prices diminishes more rapidly when the Covid period is excluded from the estimation sample. This might root in the fact that the Covid pandemic triggered a series of events that placed significant stress on global supply chains, and subsequent events, including Russia's invasion of Ukraine, added further pressure on supply chains and material deliveries.

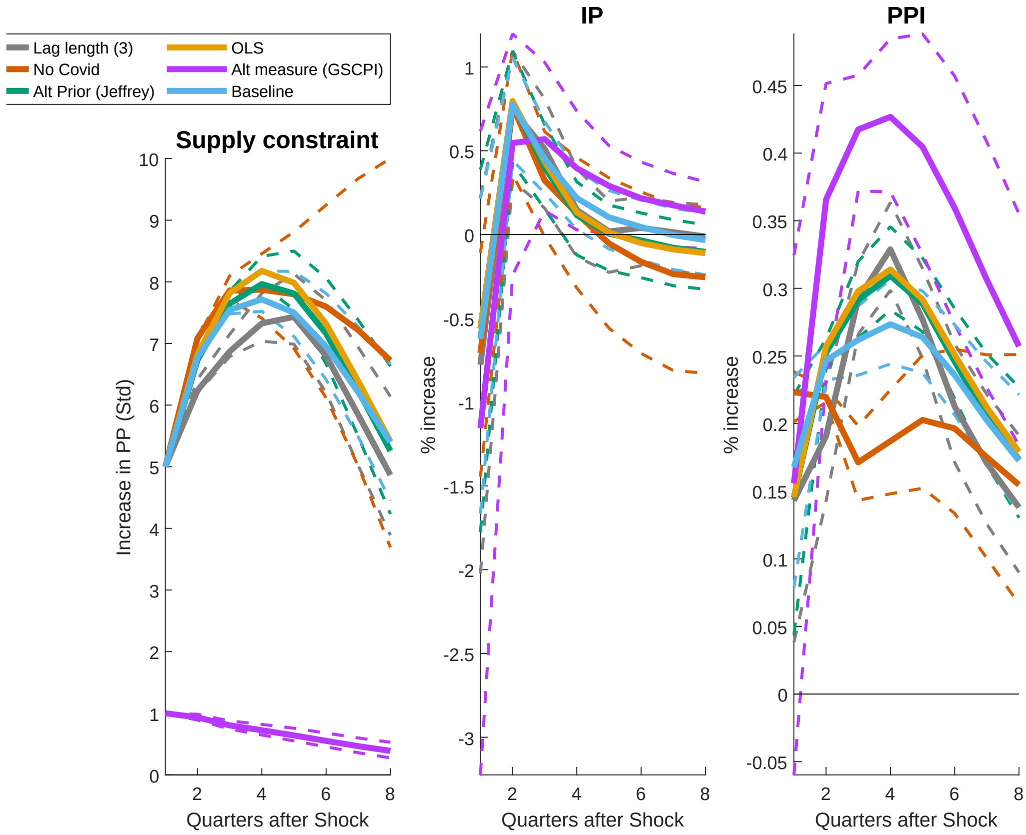



**Figure 10:** Impulse responses to a supply chain shock

*Notes:* The graph shows the impulse responses of the supply constraint measure, prices and production to a five basis point increase in the balance of firms reporting material constraints (Except for the specification including the GSCPI that shows results based on a one standard deviation increase in global supply pressure). Identification is based on the IV presented in the main text. Dashed areas show 90% confidence bands.

# 6. Discussion and Conclusion

We present a procedure for identifying a macro shock based on firm-level data. In our empirical application, we investigate the effect of a supply chain disruption, or more precisely, a lack of input material, on the German manufacturing sector. Identification of the supply chain shock relies on a combination of firm-level sign restrictions on the relation between price and production expectations and their respective realisations, coupled with additional information on production plans and demand developments. We make use of detailed firm-level survey data that allows us to track firm-level activities over time. Our results supported by firm-level data suggest that the effect of a supply chain disruption is particularly persistent on price increases, whereas the effect on production fades out quite quickly.

The empirical application of our identification approach based on microdata is but one of many potential use cases. This procedure, however, requires detailed firm-level data. We consider our proposed identification approach as a potential alternative to the common sign restriction and narrative approaches, thus ensuring that the observed firm-level responses align with the estimated aggregate effects.

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# A. Appendix: Data

## A.1. The external proxy

Table (A1) shows the average number of firms for each group used in the construction of the proxy variable.

**Table A1:** Number of observations by group

| **Group** | **Restrictive shock** | | **Loosening shock** | |
|---|---|---|---|---|
| | Material impediment | No impediment | Material impediment | No impediment |
| # Firms only impediment satisfied | 99 | 2,377 | 723 | 2,619 |
| # Firms impediment and sign satisfied | 68 | 285 | 26 | 43 |

*Notes:* The table shows the average number of firms for each group identified for the construction of our baseline instrument. The first row corresponds to the denominator and the second line to the nominator of equation (4).

# B. Appendix: Estimation