What flattens the supply curve?*

Edvin Ahlander† Mathias Klein‡ Evi Pappa§

Stockholm University Sveriges Riksbank UC3M

July 15, 2025

Abstract

We compile a unique dataset with over 20 years of monthly price and real output data for Swedish industrial firms and use it to estimate the short and medium-run responses of prices and quantities to exogenous demand shocks. A 1 percent increase in output due to demand shocks raises prices by 0.35% within a year. The supply curve's elasticity varies with economic conditions and firm characteristics. It flattens with financial uncertainty and steepens during inflationary periods. Higher supply elasticities are found in firms with low competition, labor costs, and sales volatility.

JEL classification: L11, D22, E3

Keywords: supply elasticity, firm-level data, instrumental variables, state-dependence

*We thank Guido Ascari, Adrien Auclert, Scott Baker, Anna Breman, Max Breitenlechner, Jan Bruha (discussant), Olivier Cardi, Huw Dixon, Stefano Fasani, Martin Geiger, Georgios Georgiadis, Marta Giagheddu, Nils Gottfries, Engin Kara, Caterina Mendicino, Lorenza Rossi, Anthony Savagar, Vincent Sterk, Paolo Surico, Roland Winkler and seminar participants at University of Lancaster, University of Reading, University of Innsbruck, Cardiff University, Bank of England, ChaMP Research Network Workshop, CNB Conference on Heterogeneous Agents in Macroeconomic Models, Greater Stockholm Macro Group, TGU Economics Conference 2023, University of Lund and the Nordic Heads of Research meeting for valuable comments and suggestions. Evi Pappa acknowledges financial support from Proyecto gran CEX2021-001181-M financed by MICIU/AEI /10.13039/501100011033 and PGC2018-094321-B-I00, and Comunidad de Madrid, grant EPUC3M11 (V PRICIT). The opinions expressed in this article are the sole responsibility of the authors and should not be interpreted as reflecting the views of Sveriges Riksbank.

†Stockholm University, edvin.ahlander@iies.su.se

‡Sveriges Riksbank, Research Division, mathias.klein@riksbank.se

§‡Universidad Carlos III de Madrid and CEPR, email: ppappa@eco.uc3m.es

1 Introduction

Understanding the sensitivity of prices to changes in demand is crucial for assessing the impact of demand-side policies. Estimating the slope of the supply curve reveals the extent to which demand shocks are absorbed through price adjustments instead of changes in output, quantifying the trade-off between stabilizing output and controlling inflation. The renewed interest in estimating industry-level supply curves has been sparked by recent findings, such as those by Coibion and Gorodnichenko (2015), which indicate a lack of a positive slope in the aggregate Phillips curve.

A key challenge in identifying supply curves is that prices and quantities are determined simultaneously, making it difficult to establish causal relationships through simple correlations. Researchers typically address this by conditioning their analysis on demand shifts. When demand for a product rises, both its price and output increase. However, the extent to which prices change relative to output depends on the supply curve's slope. Shea (1993) pioneered the estimation of supply elasticities by using input-output linkages to identify industries that are likely to be suitable demand-shift instruments for other industries using US data for 26 disaggregated industries. Building on this, Boehm and Pandalai-Nayar (2022), provide state-dependent estimates for supply curves that depend on the utilization rate of production.

Our research contributes to this literature. We compile a unique, firm-level dataset containing monthly data on prices and real output for a sample of Swedish industrial firms over more than two decades. We leverage this data to estimate the short- and medium-run responses of prices and quantities to exogenous demand shocks. We infer the slope of the supply curve through a simple instrumental variable regression, where cumulative price growth is regressed on cumulative sales. The instruments used include global demand shocks, such as those identified by Baumeister and Hamilton (2019), ECB monetary policy shocks, and domestic demand shocks, measured by monetary policy surprises of the Swedish central bank.

We estimate an upward-sloping supply curve, consistent with the findings of Shea (1993) and Boehm and Pandalai-Nayar (2022). Unlike Shea, who used idiosyncratic demand shocks, we em-

ploy aggregate demand shocks, potentially leading to different price responses. Our representative industry sample contrasts with Shea's data-limited approach, while Boehm and Pandalai-Nayar (2022) use industry-level data in their analysis. We find that an external demand shock increasing industry sales by 1% leads to a 0.35% price increase within a year. Firms hardly adjust prices on impact and adjust slowly. Quantities adjust faster, peaking around eight months after the shock while prices continuing to rise until about 14 months. Instrumental variable estimates of the supply curve slope are significantly higher than least-squares estimates, indicating unobserved cost shocks' role in negative price-quantity comovement during the business cycle. Our results are robust across different external shocks and their exclusion validity.

We identify how aggregate conditions impact the price elasticity of supply. We confirm Boehm and Pandalai-Nayar (2022)'s findings that spare capacity affects the supply slope in the Swedish data with some differences. Going beyond their results, we show that firm-level supply curves are significantly steeper in times of high inflation, highlighting the influence of inflationary pressures. Harding et al. (2023)'s macroeconomic model supports this convex Phillips curve behavior, and our findings align with their model. Additionally, Blanco et al. (2024)'s UK data and Klein et al. (2024) using Swedish data show increased price change frequency during the recent inflationary period, supporting our results, and suggest a non-linear Phillips curve. Finally, Arndt and Enders (2023) also observe that inflation affects price change frequency and amplifies the impact of cost and monetary policy shocks.

Moreover, we find that supply curves flatten and become even negative during high financial volatility, with firms reducing prices in response to global demand shocks under such conditions. This finding is both new and surprising. Gilchrist et al. (2017) propose a model where financial distortions prompt firms to raise prices in response to adverse financial or demand shocks. Reverting their analysis for positive shocks, our estimates suggest that firms lower prices following positive demand shocks to boost internal liquidity and avoid external financing amid high financial uncertainty. We observe no significant changes in the supply curve's slope during booms versus recessions, high macroeconomic volatility (Vavra, 2014), economic policy uncertainty, or

increased labor market tightness.

Our dataset's strength lies in its ability to reveal how firm-specific characteristics affect the supply curve slope. We find that supply curves are flatter for firms facing high competition, high sales volatility, and high labor costs. Conversely, firms with low competition and challenging market access show more responsive pricing. Specifically, exporting firms have a significantly flatter supply curve. Additionally, due to Sweden's sticky wage bargaining, firms with higher labor costs also exhibit flatter supply curves. Finally, firms with a more stable market have significantly steeper supply curves compared to those with high sales volatility.

This paper makes a significant contribution by providing firm-level supply curve estimates, demonstrating that the slope depends on both the aggregate economic state and firm-specific characteristics. Unlike Shea (1993) and Boehm and Pandalai-Nayar (2022), we use a unique monthly dataset that combines producer price index (PPI) data with firm-level production and sales data, along with additional administrative data. Recent studies of Dedola et al. (2021) estimate price adjustments along the extensive and intensive margin of production, and of Gagliardone et al. (2023) estimate the primitive New Keynesian Phillips, use similar high frequency price data for Denmark and Belgium, respectively. Relative to these papers, apart from having a different objective, our dataset extends over a longer period and includes recent inflationary trends.

Our estimates are valuable for both academics and policymakers, highlighting that firms' responses to shocks depend on the timing of the shock and the firm's characteristics. This suggests the need for state-dependent pricing models, as opposed to the constant price stickiness assumed in standard macroeconomic models like the "Calvo" model. Our findings also indicate that demand-driven policies will impact firms differently based on their competitiveness, labor costs, and sales volatility, affecting input allocation and profit distribution. This adds to existing research on the importance of heterogeneity in price stickiness (see, e.g., Carvalho and Nechio (2016) and Nakamura and Steinsson (2010)) and suggests that firm-specific supply elasticities should also be considered in macroeconomic dynamics and policy.

The rest of the paper is structured as follows: Section 2 covers data sources, data merging methodology, and summary statistics. Section 3 explains the econometric approach for estimating the price elasticity of supply. Section 4 presents baseline estimates and robustness checks. Section 5 explores non-linearities related to economic conditions and firm characteristics, and Section 6 concludes the analysis. The appendix collects detailed description of the data construction as well as results from additional exercises that we do not present in the main text for economy of space.

2 Data construction

The firm-level data on prices and real output at the monthly frequency is assembled using information from four separate microdata sources:

- The official Swedish Producer and import price index data (*Prisindex i producent- och importled*, henceforth, PPI) includes both domestic, export and import producer prices for the period January 1992 to September 2022. The unit of observation is the price of a product-level transaction.

- The official Swedish Industrial production index data (*Industriproduktionsindex*, henceforth, IPI) contains information on firms' total nominal net sales, broken down into domestic and export sales between January 1998 and September 2022. The selected firms comprise of the largest firms that together make up 95 percent of total sales and report their monthly total net sales to domestic and foreign customers in thousands of Swedish Krona (SEK).

- The Production of Commodities and Industrial Services (*Industrins varuproduktion*, henceforth IVP) survey is used in order to aggregate the product-level PPI data to the firm level, as well as to construct a measure of firms' market shares. The IVP data contains annual product-level information on delivered quantities and transaction prices between 1997 and 2020. The survey aims to provide information on how domestic industrial production

is distributed across products. Only firms with at least 20 employees are considered for the survey and sampled firms are asked to allocate their annual production value over the products they sell.

- The credit bureau Upplysningscentralen (henceforth, UC), covering the population of Swedish corporations (*aktiebolag*) annual balance sheet and income statement data is used to recover information on firms' total assets, sales, personnel costs, long-term debt and number of employees and is available between 1989 and 2020.

To study the relationship between firms' real output and price-setting, we merge PPI price data with IPI sales data. We aggregate PPI data to the firm level using IVP data and include additional variables from the PPI, IVP, and UC datasets to assess firm-level heterogeneities. The final baseline dataset covers the period January 2001 until December 2021.[1] Section A.1 in the Appendix details our data cleaning procedures, variable definitions, and confirms the representativeness of our sample.

The final sample of firms in the merged IPI-PPI dataset faces two main bottlenecks. First, not all firms overlap between the PPI and IPI datasets, leading to a monthly loss of some firms. Second, we require that observed PPI products account for at least half of a firm's annual production value to aggregate PPI data to the firm level, resulting in further sample reduction. Data cleaning significantly reduces the sample size, especially in the first ten years (see Figure A.1 in the Appendix).[2] Table A.1 and Table A.2 in the Appendix indicate that firms in the merged sample are not statistically different from those in the individual IPI or PPI samples, despite the reduced sample size.[3] Figure A.2 shows that the average monthly year-on-year percentage changes in prices and net sales in the merged sample closely track the trends in the full PPI and IPI samples.

[1] Below, we present results when extending the data until September 2022.

[2] We confirm the robustness of our results by starting the sample in 2010 (see Figure A.4), finding no sensitivity to sample size.

[3] The merged sample tends to include larger and more productive firms, possibly due to the exclusion of firms with fewer than 20 employees in the IVP data.

3 Empirical approach

Our objective is to estimate firm-level supply curves using the comprehensive panel data outlined in the previous section. Specifically, we aim to estimate the following equation:

$$p_{i,t} = \alpha_i + \alpha_m + \eta_P q_{i,t} + u_{i,t}$$

where $p_{i,t}$ and $q_{i,t}$ represent the prices and quantities for firm i in month t, respectively. The terms α_i and α_m are firm and month fixed effects, capturing unobserved firm-specific variations and seasonal patterns. The variable $u_{i,t}$ denotes a supply shock, and η_P is the inverse elasticity of supply, which we aim to estimate.

Supply shocks, $u_{i,t}$, typically result in a downward bias in the OLS estimates of η_P, as they tend to move quantities and prices in opposite directions. In contrast, demand shocks generally move prices and quantities in the same direction. To address this bias, instruments that influence industry demand without affecting supply are usually employed. However, finding relevant and perfectly exogenous instruments can be challenging.

To address this challenge, we use an external instrument that reflects global industrial production changes: the Baumeister and Hamilton (2019) series of global economic activity shocks. These shocks, identified in a Bayesian VAR on the oil market using sign restrictions, simultaneously increase oil production, world industrial production, and oil prices.[4]

The global economic activity shock can serve as a demand disturbance for Swedish firms catering to the domestic market. An exogenous increase in global economic activity boosts demand for Swedish exports, thereby increasing export sales. This rise in export demand, in turn, elevates demand for Swedish intermediate products, leading to increased domestic sales—a key exogenous variation in our analysis. Similar approaches have been used by Boehm and Pandalai-Nayar (2022), who utilize foreign demand variations to estimate industry-level supply curves, and by

[4]In addition to global economic activity shocks, Baumeister and Hamilton (2019) also identify oil demand and oil supply shocks in their model.

Shea (1993), who construct instruments from changes in downstream demand using input-output linkages.

Additionally, we consider two other instruments: (a) ECB monetary policy shocks identified via a high-frequency approach by Jarociński and Karadi (2020), and (b) Swedish monetary policy shocks identified similarly by Laséen and Nilsson (2024). As we demonstrate below, the core results remain consistent regardless of whether we use these monetary policy shock series or our baseline global economic activity shock.

To estimate the supply elasticity, we follow the approach of Barnichon and Mesters (2021) by analyzing the relationship between price and sales. Specifically, we examine the cumulative change in price inflation resulting from an external shock that increases sales growth by 1 percentage point at various time horizons, denoted as h.[5]

Throughout this paper, we use monthly data and include firm and month fixed effects in our regressions. Due to the high volatility of firm-level price and sales data, we apply a three-month moving average to both series in our estimations. We also cluster standard errors at the firm level to account for potential correlations within firms over time.

The panel local projection instrumental variable regression (LP-IV) we estimate takes the following form:

$$\sum_{j=0}^{h} \pi_{i,t+j} = \alpha_{i,h} + \alpha_{m,h} + {\eta_P}^h \sum_{j=0}^{h} \Delta sales_{i,t+j} + \gamma_h \sum_{p=1}^{6} X_{i,t-p} + \theta_h \sum_{l=0}^{6} Z_{t-l} + u_{i,t,h}, \qquad (1)$$

where $\pi_{i,t+j}$ is the change in prices of firm i between t and $t+j$ and $\Delta sales_{i,t+j}$ is the change in real sales of firm i between t and $t+j$. X_i is a vector of additional firm-level controls. Here, we include six lags of price changes and sales growth. Moreover, Z is a vector of additional aggregate control variables which includes the aggregate real oil price and unit labor cost.

The elasticity ${\eta_P}^h$ quantifies how prices respond to an external shock that increases sales by 1

[5]Barnichon and Mesters (2021) use this method to estimate the Phillips multiplier, which describes the relationship between changes in aggregate unemployment and inflation, akin to the government spending multiplier in fiscal studies (Ramey and Zubairy, 2018).

percentage point over the next h periods. A significant advantage of this approach is that it allows us to estimate the elasticity using an instrumental variables (IV) regression. Yet, the global economic activity shock identified by Baumeister and Hamilton (2019) that serves as our instrument for external demand is defined using sign restrictions, which assume that it simultaneously increases world industrial production, oil production, and oil prices. Hence, the resulting rise in oil prices could directly or indirectly affect firms' cost structures by increasing unit labor costs, potentially violating the exclusion restriction on the supply curve. To address this, we control for current and past values of real oil prices and unit labor costs in our baseline model.

4 Results

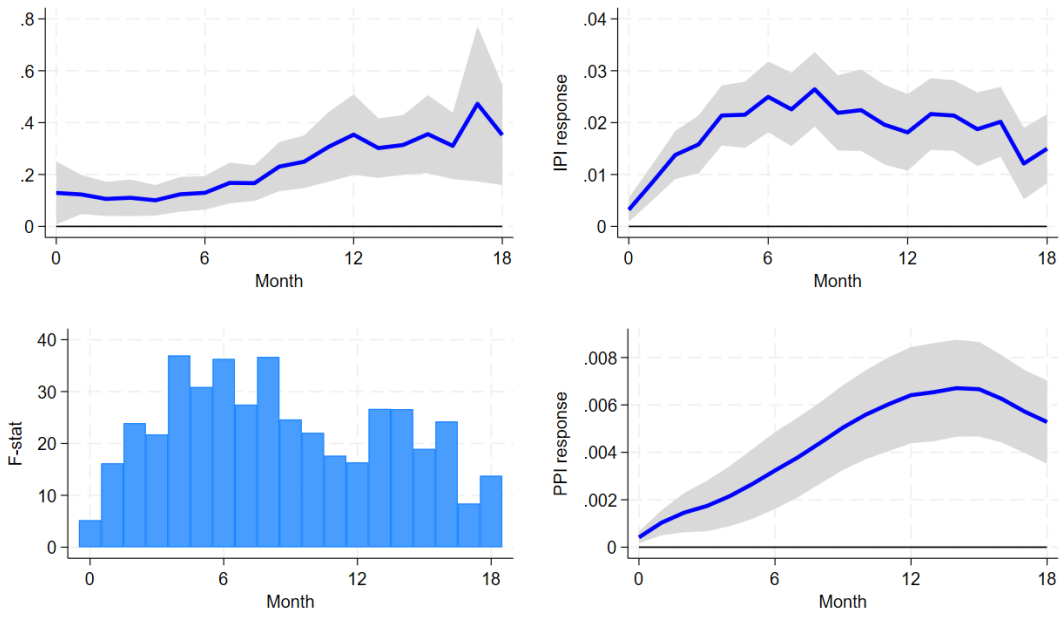
4.1 Baseline

Figure 1 illustrates our baseline estimates for the average slope of the firm's supply curve elasticity over different horizons, ranging from $h = 0$ to $h = 18$ (top left panel). Additionally, it displays the F-statistics from the first stage of the instrumental variable regression, as described in Equation (1), computed using the methodology outlined by Montiel-Olea and Pflueger (2013) (lower left panel).

The F-statistics indicate the degree of correlation between the global demand shock and cumulative sales changes at various horizons, h. For most horizons, the F-statistic significantly exceeds 10 and surpasses the serial correlation robust threshold established by Montiel-Olea and Pflueger (2013), which requires F-statistics above 23 for horizons between $h = 3$ and $h = 10$. This suggests that weak instruments are unlikely to pose a significant issue for our analysis.

As depicted in the upper left panel, the supply elasticity is estimated to be positive upon impact and increases over time. One year after the shock, the supply elasticity reaches approximately 0.35. This estimate aligns with the findings of Shea (1993) and Boehm and Pandalai-Nayar (2022), who used different instruments and methodologies to estimate supply elasticity. For

Figure 1: Baseline Results



Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=18. Shaded areas correspond to the 90% confidence region. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. The top and bottom right panels present impulse responses for average price (bottom panel) and sales growth rates (top panel) estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. We cluster standard errors at the firm level. The sample is 2001m1-2021m12.

instance, Boehm and Pandalai-Nayar (2022) reported an estimate of 0.24 using U.S. industry data, which falls within the confidence bands of our estimate despite differences in data and methodologies. Additionally, our estimates indicate that the supply elasticity reaches 0.4 and is statistically significant one and a half years after the shock.[6] This finding suggests that firms continue to raise prices relative to output for over a year following the initial shock.

The impulse responses for average sales growth and inflation, which underlie the supply curve multiplier, are obtained from OLS regressions of sales growth and inflation on an external demand shock. These responses are presented in the top right and bottom right panels of Figure 1,

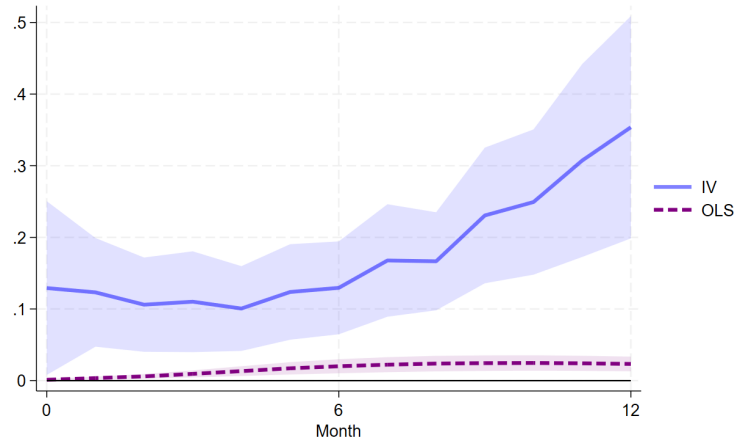
[6]We cluster standard errors at the firm level. For robustness, we also present results using weak instrument robust methods to compute the confidence sets for supply elasticity in Figure A.5 in the appendix (see Barnichon and Mesters (2021) for details).

respectively. According to these estimates, both prices and sales respond significantly to the external shock. Consistent with the notion of sticky prices, the peak price response occurs later than the peak output response, at 14 months and 8 months, respectively. At the end of the forecast horizon, prices exhibit a more persistent response relative to sales, resulting in an upward-sloping supply curve, as shown in the upper left panel.

4.2 IV versus OLS estimates

Figure 2 displays the estimated supply elasticity (solid line) alongside its unconditional counterpart (dotted line), derived from an OLS regression of average price growth on average sales growth without the use of an instrument. The contrast between the estimated elasticities is striking: the identified slope is substantially larger in absolute value than the slope suggested by the OLS estimate. This discrepancy is consistent with expectations in the presence of confounding supply shocks, which tend to cause a positive correlation between sales and prices. A similar finding is discussed by Shea (1993).

Figure 2: IV versus OLS



Notes: Estimated average supply curve using Baumeister and Hamilton (2019) global demand shocks as instruments (continuous line). The dotted lines depict the unconditional estimated slope using OLS. The sample is 2001m1-2021m12 and standard errors are clustered at the firm level.

4.3 The exclusion restriction

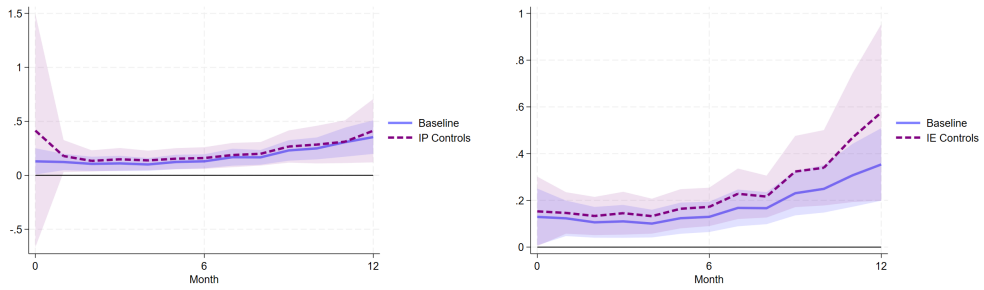
As previously discussed, the global economic activity shock identified by Baumeister and Hamilton (2019), which we use as an instrument for external demand, also impacts oil prices. Consequently, the increase in oil prices could alter firms' cost structures, potentially violating the exclusion restriction on the movement of the supply curve. To address this concern, we control for oil price fluctuations in our baseline regression.[7] While these shocks could theoretically encompass changes in both global demand and supply, our estimates in Figure 1 indicate significant increases in both firm-level prices and sales in response to the identified shock. This suggests that supply disturbances play a minor role.

Nonetheless, we aim to directly address this potential endogeneity issue. Fortunately, the PPI price dataset includes information on the market (import, domestic, export) for each specific product. In our analysis, we have primarily used the domestic market price as the main outcome variable. However, since we also have data on import prices, we can control for changes in firms' costs originating from the international market, which may be a primary confounding factor when examining shocks originating from the global economy. Although we lack corresponding quantity information for these import prices, we can construct an unweighted average of the observed import prices at the firm level and include this measure as an additional control variable in the baseline regression. Specifically, we incorporate the contemporaneous value and six lags of firm-level import price changes into Equation (1) as additional controls.

Ideally, we would have included this control in our baseline regressions. However, some firms that operate domestically may not import goods at all. Additionally, to run our modified regression, we require information on both import and domestic prices. Given these constraints, including import prices in the main analysis would result in a loss of roughly 60% of our observations. Despite this limitation, the results presented in the left panel of Figure 3 demonstrate that the estimated slope of the supply curve remains nearly identical to the slope obtained without

[7] Additionally, Baumeister and Hamilton (2019) find that the identified global economic activity shocks account for only a small fraction of oil price variations, suggesting that the cost of intermediates does not change significantly following these shocks.

Figure 3: Controlling for Changes in Import Prices and Inflation Expectations



Notes: Estimated average supply curve using Baumeister and Hamilton (2019) global demand shocks as instruments (continuous line). Panel a) The dotted lines depict the estimated slope when we also control for six lags in import price inflation. Panel b) The dotted lines depict the estimated slope when we also control for six lags of inflation expectations. The sample is 2001m1-2021m12 and standard errors are clustered at the firm level.

controlling for import price movements. Figure A.6 in the appendix provides the F-statistics and responses for prices and quantities associated with this analysis. Even with the reduced sample size, the F-statistics remain high, and the estimates for individual responses and elasticities are statistically unchanged.

There may also be concerns that the external demand shocks we examine could influence firms' pricing decisions not only through demand effects but also by altering firms' expectations about future inflation. Unfortunately, our sample does not include firm-level data on inflation expectations. However, it seems unlikely that these transient shocks would significantly affect firms' inflationary expectations, especially given the Swedish monetary policy regime. To ensure that our results are not driven by changes in expectations, we re-ran our baseline regression specified in Equation (1), controlling for the contemporaneous value and six lags of aggregate inflation expectations obtained from the Economic Tendency Survey of the National Institute of Economic Research (Konjunkturinstitutet). Specifically, we used monthly seasonally adjusted expectations regarding domestic selling prices for the upcoming three months among firms in the Swedish manufacturing sector (Question 202). The estimated supply elasticities for different horizons are reported in the right panel of Figure 3. The results indicate that the estimates of price supply elasticity remain statistically unchanged; if anything, the magnitude of the elasticity increases

when we control for inflation expectations after 12 months.[8]

4.4 Other instruments

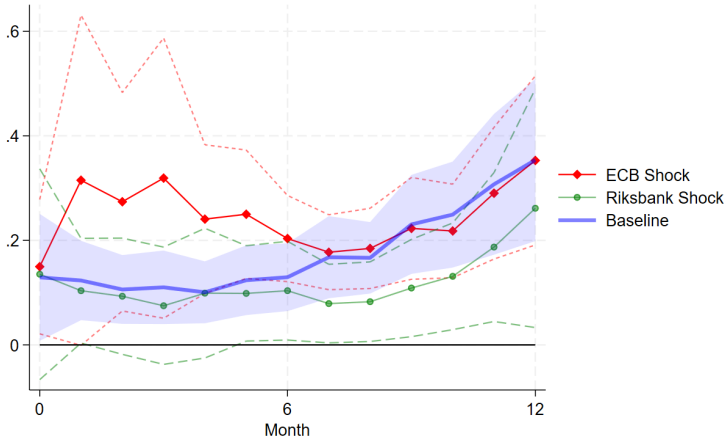
The estimates presented thus far suggest a relatively elastic supply curve. However, these results might be influenced by the specific instrument used to measure demand shifts. To determine whether our estimates are robust to the choice of instrument, we re-estimate Equation (1) using the ECB monetary policy shocks identified by Jarociński and Karadi (2020) as an alternative instrument for capturing changes in firms' demand. The rationale for using this instrument is that expansionary monetary policy in the Euro Area—a significant trading partner for the Swedish economy—should boost demand for Swedish goods. Additionally, due to international linkages in the manufacturing sector, such policy measures are likely to increase demand for Swedish domestic products as well.

The continuous blue line in Figure 4 represents our baseline estimates of the supply elasticity, while the red diamond line shows the estimates obtained when using ECB monetary policy surprises as the instrument for demand changes. The two instruments yield similar estimates, with no statistically significant differences in elasticity. However, the supply elasticity is estimated to be higher during the first six months when using the ECB shocks compared to the global demand shock instrument. In the appendix (Figure A.7), we also provide the F-statistics for the ECB shock instrument. Although the instrument is somewhat weaker during the first two months—resulting in wider confidence bands for the estimated supply slope during this period—the overall magnitude of the slope, as well as the dynamics of price and sales growth, are not statistically different from the baseline.

Additionally, we consider domestic monetary policy shocks as instruments for changes in domestic demand. We use the series constructed by Laséen and Nilsson (2024), which follows the

[8] Additionally, although not presented here due to space constraints, we find that the response of inflation expectations and the F-statistics for the first-stage regression of aggregate inflation expectations to the global shock are nearly zero for the first six months following the shock. This finding reinforces our confidence in the validity of the exclusion restriction.

Figure 4: Robustness: ECB and Swedish Monetary Policy Shocks



Notes: Estimated average supply curve using Baumeister and Hamilton (2019) global demand shocks as instruments (continuous blue line). The green-circled lines depict the estimated slope when we use the Riksbank monetary policy shock as an instrument for changes in domestic demand and the red diamond line the case we use the Jarociński and Karadi (2020) ECB monetary policy shock as an instrument for changes in foreign demand. The sample is 2001m1-2021m12 and standard errors are clustered at the firm level.

methodology of Bu et al. (2021) to identify monetary policy changes using Swedish data.[9] The estimated supply elasticity, using the Swedish monetary policy shocks as an instrument, is depicted by the green-circled line in Figure 4. While these estimates do not substantially differ from the benchmark estimates, they are less precise due to weaker F-statistics in the first stage for this instrument (see Figure A.8 in the appendix).

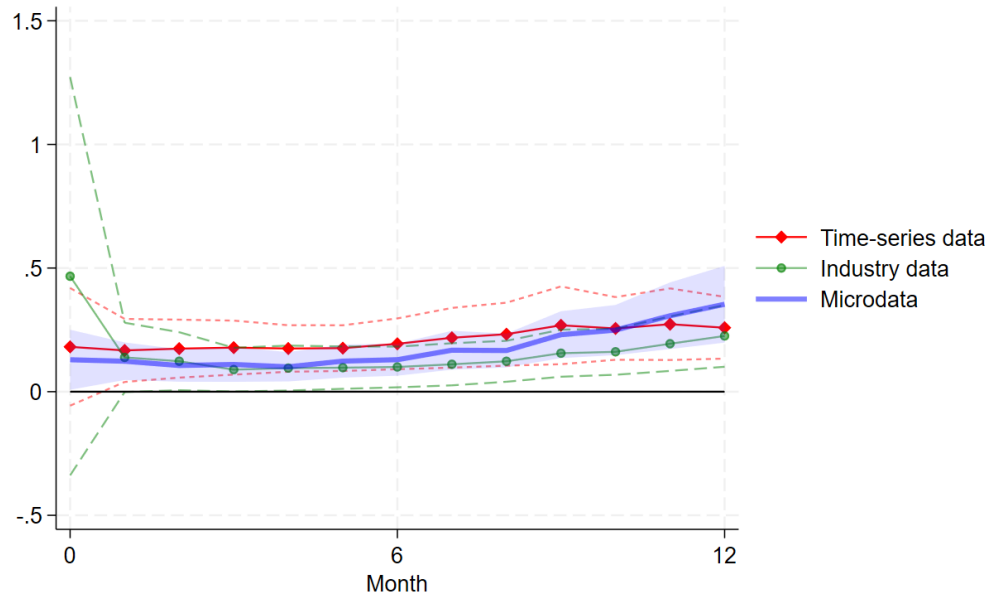
Overall, the analysis in this section suggests that, regardless of the instrument used, the supply elasticity is positive. All estimates converge on an average supply elasticity of approximately 0.3 one year after the shock.

[9] In the specification for the Swedish monetary policy shock, we control for six lags of the Swedish unemployment rate and the log difference of the IMF's commodity price index (including all commodities) and in the specification for the ECB shock we control for the EUR/SEK exchange rate.

4.5 Macro and industry versus firm-level data

In Figure 5 we plot the estimated supply elasticity if we repeat our exercise by using aggregate (time series) data and the same identification approach (red diamond line). Thus, for this exercise we rely solely on time series variation.

Figure 5: Micro versus Macro Data



Notes: Estimated average supply curve using Baumeister and Hamilton (2019) global demand shocks as instruments and i) firm level data -continuous blue line -ii) industry data - green-circled line and iii) aggregate data - red diamond line.

The figure indicates that the estimated slope does not differ statistically when using either micro-level or aggregate time series data. In the appendix (Figure A.9), we provide detailed F-statistics and impulse response estimates for this analysis. It is evident that the use of aggregate data suggests the presence of weak instruments, whereas the additional information provided by the micro data mitigates this issue without significantly altering the quantitative results.

Furthermore, given that prior studies in the literature have typically used industry-level data to estimate supply curves, we replicate our analysis by aggregating firms in our sample at the

industry level. Specifically, we aggregate the data to the 2-digit industry level according to the Swedish Standard Industrial Classification (SNI), resulting in 26 distinct industries. The Producer Price Index (PPI) data is aggregated by calculating a weighted arithmetic average of all prices, using official product-specific PPI weights, while the Industrial Production Index (IPI) is aggregated by summing the total output across all firms within each industry-month. The green-circled lines in Figure 5 display the results of this exercise. Once again, the additional detail provided by micro data enhances the precision of the estimates without substantially affecting the estimated magnitude of the supply elasticity.

5 Non-linearities

Any textbook analysis would emphasize that the elasticity of supply is not constant; it varies based on numerous factors. Leveraging the richness of our data, we explore economic determinants that might influence the supply elasticity of firms both at an aggregate level (Section 5.1) and at an individual level (Section 5.2).

To investigate potential state-dependencies in supply elasticity across time and among firms, we extend the linear specification (1) by estimating a series of interacted panel local projections instrumental variables (LP-IVs) models, structured as follows:

$$\begin{aligned}\sum_{j=0}^{h} \pi_{i,t+j} =& I_{i,t-1} \left[P_h^A \sum_{j=0}^{h} \Delta sales_{i,t+j} + \gamma_h^A \sum_{p=1}^{6} X_{i,t-p} + \theta_h^A \sum_{l=0}^{6} Z_{t-l} + \alpha_{i,h}^A + \alpha_{m,h}^A \right] \\ &+ (1 - I_{i,t-1}) \left[P_h^B \sum_{j=0}^{h} \Delta sales_{i,t+j} + \gamma_h^B \sum_{p=1}^{6} X_{i,t-p} + \theta_h^B \sum_{l=0}^{6} Z_{t-l} + \alpha_{i,h}^B + \alpha_{m,h}^B \right] + u_{i,t,h}. \end{aligned} \tag{2}$$

In this equation, $I_{i,t-1}$ is a dummy variable representing the specific interaction of interest. For instance, when examining state-dependencies over time such as the aggregate level of capacity

utilization, as done by Boehm and Pandalai-Nayar (2022), $I_{i,t-1} = I_{t-1}$, indicates that the state is consistent across firms but varies over time. Conversely, when analyzing firm-specific characteristics like market power or productivity that may significantly influence supply elasticity, the interaction dummy varies across both firms and months. To mitigate contemporaneous correlations between aggregate shocks and the state variable, we include a one-period lag of $I_{i,t-1}$ in the regressions. In this framework, P_h^A estimates the supply elasticity in state A, while P_h^B captures the supply elasticity in state B.

5.1 Supply Curves and the State of the Economy

In this section, we explore three macroeconomic factors that influence the magnitude of firms' supply elasticity: (i) capacity utilization, (ii) the level of aggregate inflation, and (iii) the state of the macroeconomy.

Capacity Utilization

Boehm and Pandalai-Nayar (2022) demonstrate that spare capacity utilization is a critical determinant of supply elasticity. They find that industries operating near full capacity exhibit a steeper supply slope compared to those with more slack. Their estimation strategy hinges on the premise that plants constrained by capacity limitations react differently to demand shocks than those with excess capacity. Consequently, the proportion of constrained plants influences an industry's price and production responses to such shocks. Specifically, they allow industries' price responses to depend on their initial utilization rates.

Building on their approach, we examine whether capacity utilization constraints affect the estimated price elasticity of supply in our sample, using firm-level data instead of industry-level data. We define the dummy variable in Equation (2) as one if the aggregate quarterly series for total industrial capacity utilization (*Industrins kapacitetsutnyttjande*) from Statistics Sweden is above the 75th percentile and zero if it is below. This dummy variable is lagged by one period to pre-

vent immediate impact from shocks, in line with the methodology of Boehm and Pandalai-Nayar (2022).

The upper panel of Figure 6 depicts the average estimates under two regimes: high capacity utilization (solid line) and low capacity utilization (dotted line). Our findings only partially confirm the results of Boehm and Pandalai-Nayar (2022), as we observe higher price elasticity of supply during periods of high capacity utilization, although the difference in estimated coefficients is not statistically significant[10]. The F-statistics for the first-stage regression and the impulse responses of price and sales growth are shown in Figure A.10 in the Appendix. The right panel of Figure A.10 illustrates that, although quantities react more and prices less under excess capacity, the differences are negligible between the two regimes. Notably, during periods of high utilization, low F-statistics result in wide confidence intervals around the estimates.

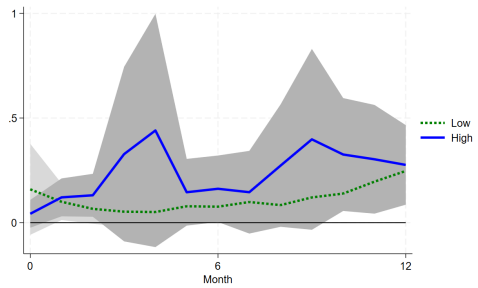
Inflation Surge

Next, we investigate how inflation surges influence firms' price elasticity of supply. The baseline regression dataset concludes in December 2021 due to the unavailability of product weights for 2022. However, we extend the sample to September 2022 by assuming that product weights remain unchanged from the previous year, a reasonable assumption given their typical year-to-year stability. This extension allows us to assess the impact of the inflation surge experienced in Sweden in 2022 on the estimates of price elasticity of supply, since during the first half of 2022, inflation increased significantly, rising from around 3.9% in January to 9.7% in September. The middle panel of Figure 6 presents the results of this analysis.

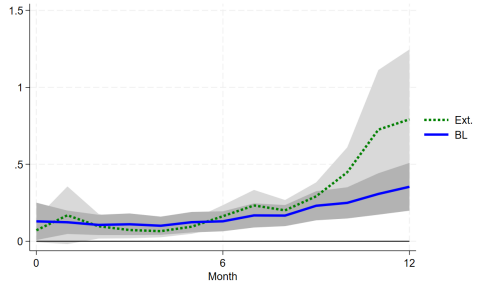
Extending the sample to include the recent surge in inflation significantly increases the estimated supply elasticity of firms, particularly between 10 and 14 months after the demand shock (see Figure A.11). In Figure A.11 in the Appendix, we demonstrate that the instrument remains strong for the extended sample. The analysis reveals that average price responses were more sluggish,

[10]For brevity, we do not present additional results here, but they indicate that excluding oil prices as a control variable reveals statistically significant differences in slope between the two regimes, aligning with the findings of Boehm and Pandalai-Nayar (2022).

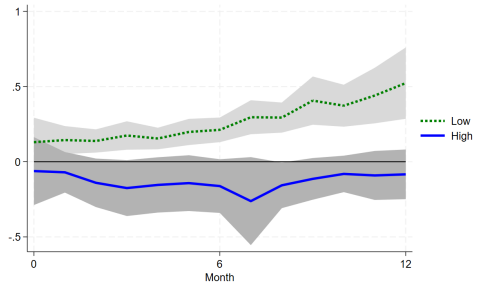
Figure 6: The supply Elasticity and Macroeconomic Conditions



High vs. Low Capacity Utilization



Including the Inflation Surge



High vs. Low Financial Uncertainty

Notes: Estimated average supply curve using Baumeister and Hamilton (2019) global demand shocks as instruments. Top panel: Dotted lines characterize months for which capacity utilization is above its 75 percentile and blues continuous lines months for which the industrial utilization rate is below the 75 percentile in the sample. Middle panel: Continuous line for the sample 2001m1-2021m12. Dotted lines depict the estimated slope when we extend the sample to 2022m9 assuming equal product weights between 2021 and 2022. Bottom panel: Dotted lines characterize months for which the EU STOXX is above its 75 percentile and blues continuous lines months for which the EU STOXX is below the 75 percentile in the sample. Standard errors are clustered at the firm level.

while quantity responses initially reacted faster during the high inflation period but slowed six months post-shock. These findings are crucial for monetary policymakers, as they highlight that

firms are more likely to adjust prices in response to demand pressures when inflation spikes. This result aligns with recent work by Bunn et al. (2022), who observed a non-linear pricing response in UK firms during recent periods of high inflation. Our estimates indicate that, 10 to 14 months after a demand disturbance, firms tend to alter prices more significantly than quantities, steepening the average supply curve.

Financial Uncertainty

Firms' decisions can also be influenced by financial uncertainty, as discussed by Gilchrist et al. (2017). We investigate the impact of financial uncertainty on firms' pricing and sales decisions in response to demand shocks. For this purpose, we set the dummy variable in Equation (2) to one when the EU STOXX index volatility exceeds its 75th percentile and zero otherwise, then re-estimate the regression. Given Sweden's status as a small open economy, we assume that financial uncertainty in European markets affects Swedish financial uncertainty[11]. The estimated supply elasticities are shown in the last panel of Figure 6.

During periods of high financial uncertainty, the price elasticity of supply is negative and statistically indistinguishable from zero. In contrast, during periods of low financial uncertainty, the estimated supply elasticity is significantly higher, reaching 0.2 six months after the shock and 0.5 one year after the shock. However, during high financial uncertainty, the elasticity estimate remains at -0.2 and is not significantly different from zero across all horizons. These findings indicate substantial differences in firms' price supply elasticity across financial uncertainty regimes. As illustrated in Figure A.12 in the Appendix, these differences are driven by varying pricing decisions. Specifically, firms tend to increase prices and quantities in response to demand shocks during normal times, but decrease prices during high financial uncertainty. This is consistent with the findings of Kumar et al. (2023), who, through a randomized control trial in New Zealand, found that increased uncertainty leads firms to reduce prices, employment, investment, and sales, while becoming less likely to adopt new technologies.

[11] We also experimented with the VIX index, and similar results are presented in Figure A.13 in the Appendix.

The uncertainty studied by Kumar et al. (2023) is macroeconomic, whereas in Sweden, financial uncertainty prompts firms to lower prices following a demand shock—a surprising and novel result. Gilchrist et al. (2017) propose a model where financial distortions incentivize firms to raise prices during adverse financial or demand shocks, as observed during the Great Recession. Our findings accord with the predictions of their model for positive demand shocks: In times of high financial uncertainty, firms may lower prices post-shock to enhance internal liquidity and avoid external financing.

Macroeconomic and Policy Uncertainty

Macroeconomic uncertainty can also influence firms' decision-making processes. Vavra (2014) shows, using CPI microdata, that firms exhibit greater desired price changes during periods of high volatility. We explore whether macroeconomic uncertainty impacts firms' pricing and sales decisions in response to demand shocks by setting the dummy variable in Equation (2) to one during the Great Financial Crisis, the EU sovereign debt crisis, and the COVID crisis, and zero otherwise. Unfortunately, the first-stage F-statistics for high macroeconomic uncertainty are very low, as shown in Figure A.14 in the Appendix, preventing robust inference.

As an alternative, we investigate the influence of policy uncertainty on firms' pricing and sales decisions following a demand shock. Figure A.15 in the Appendix indicates that Swedish economic policy uncertainty, measured by the EPU index from Armelius et al. (2017), does not significantly affect firms' pricing behavior.

The state of the economy and the labor market

The state of the economic cycle might also affect firms' pricing decisions. According to Pigou (1927) and Keynes (1939), increases in aggregate demand can have minimal effects on prices and significant effects on output, as firms behave more competitively during economic booms. On the other hand, Chevalier and Scharfstein (1994) suggest that firms in customer markets experiencing

liquidity squeezes may maintain or even raise prices during recessions to boost current cash flows, sacrificing future sales. We examine these hypotheses by estimating Equation (2) during recessions versus expansions. We define recessions as periods when the unemployment rate is above its 75th percentile and when the labor market is tight, with the vacancy-to-unemployment ratio above its 75th percentile. Our findings, presented in Figures A.16 and A.17 in the Appendix, show that supply elasticity is much higher when unemployment is low, but the estimates lack precision. Additionally, the tightness of the labor market does not significantly impact the firms' supply elasticity.

5.2 Supply Curves and Firms' characteristics

The previous section demonstrated that the state of the business cycle and macroeconomic uncertainty do not significantly influence firms' pricing behavior. Instead, financial uncertainty and inflation levels are pivotal in determining the average slope of the supply curve at the firm level. Beyond examining how aggregate conditions affect supply decisions, our data allow us to explore whether specific firm characteristics significantly impact the estimated slope of the supply curve and how these characteristics influence firms' price-setting behavior. We delve into this analysis in the following sections.

Exporting Firms

We begin by investigating whether exporters exhibit different supply elasticity compared to domestic producers. Understanding whether the demand for exports is price elastic or inelastic is crucial for both marketing strategies and government policy decisions. One might expect exporters to have lower supply elasticity due to increased competition in foreign markets. Given that our data includes information on prices and sales for exporting firms, we can test this hypothesis using Swedish data. However, a challenge arises in estimating this elasticity because we lack precise information on the weight of each product in total exported sales for a given firm. To address this, we assume that the product weights are similar to those used in the domestic

price analysis.

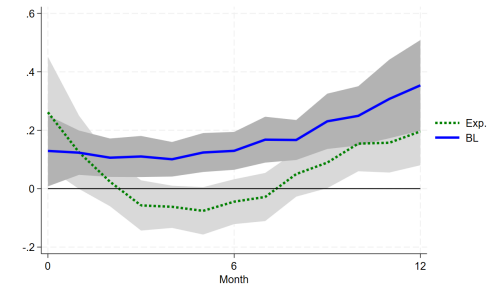
The top left panel of Figure 7 shows the estimated supply elasticity for the baseline case (continuous blue line) and for exporters (dotted green line). In Figure A.18 in the Appendix, we provide F-statistics and impulse responses for sales growth and export prices in response to the identified shock. The results indicate that the price elasticity of supply for exporters is generally lower than that for domestic producers. Specifically, the elasticity is close to zero between two and eight months following the shock but becomes positive and statistically significant ten months after the shock. This finding supports our intuition that exporters adjust their prices less frequently due to competition in foreign markets. Figure A.18 illustrates that export prices remain relatively unresponsive for approximately eight months post-shock, after which they begin to increase, resulting in significant supply elasticities.

Market Share

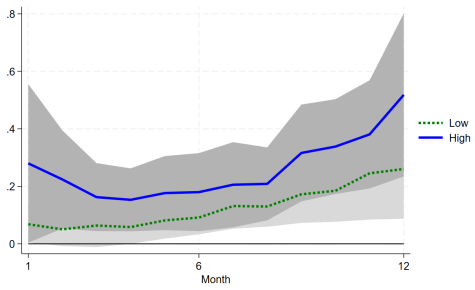
The results of the previous section suggest that market competition significantly influences the price elasticity of supply. In highly competitive markets, such as export markets, suppliers are more inclined to adjust production levels in response to demand changes rather than altering prices, resulting in lower supply elasticity. Conversely, less competitive markets may exhibit higher supply elasticity. Our dataset includes information on firms' market shares, defined as the ratio of a firm's sales to total sales within a specific product group. This allows us to explore whether supply elasticity varies with market share.

Specifically, we define market share as the proportion of sales within 4-digit product codes, based on the Combined Nomenclature (CN) classification, for a given year. The annual sales data is sourced from the IVP. For firms operating in multiple markets, we calculate a weighted average of the firm's market shares, using total sales within each market as weights. We then compute the market share for each firm annually and re-estimate Equation (2) using a dummy variable. This dummy is set to one if a firm's market share is above the 75th percentile of the distribution

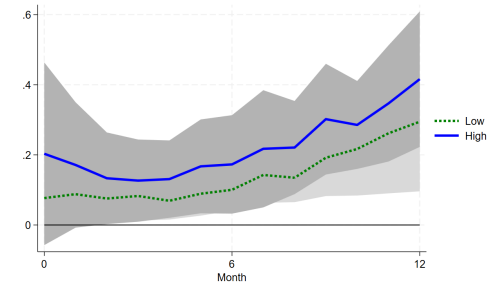
Figure 7: The Supply Elasticity and Firms' Characteristics



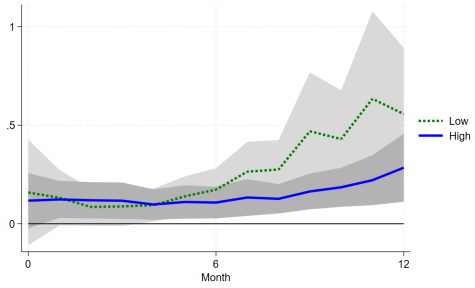
Panel a) Exporters vs. Domestic Producers



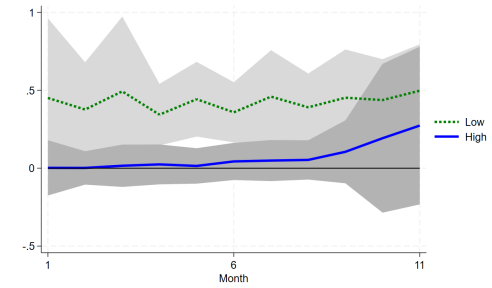
Panel b) High vs. Low market share



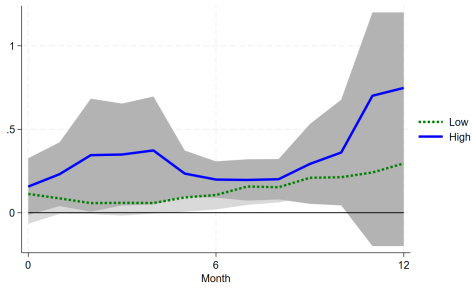
Panel c) High vs. low productivity



Panel d) High vs. Low sales volatility



Panel e) High vs. Low labor costs



Panel f) High vs. Low Leverage

Notes: Estimated average supply curve using Baumeister and Hamilton (2019) global demand shocks as instruments for domestic prices and sales in alternative specifications. Panel a) The blue continuous line corresponds to the baseline model. The dotted green line depicts the estimated elasticity when we restrict the sample to export prices and sales growth. Panel b) High (blue continuous line) versus low (dotted green line) firm market share. Panel c) High (blue continuous line) versus low (dotted green line) firm productivity, measured by sales per employee. Panel d) High (blue continuous line) versus low (dotted green line) firm sales volatility. Panel e) High (blue continuous line) versus low (dotted green line) firm labor costs. Panel f) High (blue continuous line) versus low (dotted green line) firm leverage. Standard errors are clustered at the firm level. The sample period is 2001m1-2021m12.

in the previous year and zero otherwise.[12]

[12]This method allows firms to switch groups between different years in the sample period.

The estimated supply elasticities for firms with high market shares are depicted by continuous blue lines, while those for firms with low market shares are shown by dotted green lines in the upper right panel of Figure 7. The findings indicate that firms with higher market shares tend to have a higher average supply elasticity, although the differences are not statistically significant. This outcome is primarily because firms with low market shares do not significantly adjust prices in relation to sales following a demand shock. These results align with the intuition that firms with substantial market shares typically possess a strong competitive advantage, as noted by Buzzell et al. (1975). Such firms are generally larger, better funded, and more recognizable, giving them better access to resources and allowing them to remain competitive even amid adverse shocks.

Productivity

Next, we examine the differences in supply elasticity between the most productive firms and others in our sample. Productivity is measured as the ratio of total sales to the number of employees for each firm, based on annual balance sheet data. As before, we set the dummy variable in Equation (2) to one if a firm's productivity is above the 75th percentile of the distribution from the previous year and zero otherwise.

The results, displayed in the middle left panel of Figure 7, show that more productive firms exhibit a higher average supply elasticity, indicating a greater propensity to adjust prices relative to competitors in response to demand shocks (see also Figure A.20 in the Appendix). However, these differences are not statistically significant.

Sales volatility

The prior section showed that macroeconomic volatility did not influence firms' supply elasticity. However, macroeconomic volatility does not necessarily correlate with firm-level sales volatility (see Comin and Philippon (2005)). Here, we investigate whether firms with varying levels of sales volatility react differently to demand shocks.

We define sales volatility as the one-month lagged standard deviation of year-on-year growth rates in monthly sales (from the IPI data) for each firm. Firms are then classified based on whether their volatility is above the 75th percentile cutoff. Unlike previous analyses, this classification does not allow firms to switch groups between different years. The estimated supply elasticities, shown in the middle right panel of Figure 7, indicate that firms with low sales volatility exhibit a much steeper supply curve. The difference in elasticities between low and high volatility firms is statistically significant. Bachmann et al. (2019), using German ifo Business Climate Survey data, found that increased firm-level volatility significantly influences the likelihood of price adjustments, leading to larger price changes and greater price dispersion. As shown in Figure A.21 in the Appendix, firms with high sales volatility adjust both prices and quantities more significantly in response to identified demand shocks, resulting in a lower estimated supply elasticity.

Labor costs

In the standard New Keynesian model, inflation is influenced by firms' costs, as prices are typically set as a markup over marginal costs. Since labor costs constitute a significant portion of a firm's total expenses, their fluctuations are crucial for inflation dynamics. An essential measure of labor cost is unit labor costs, defined as total labor costs per unit of output. The behavior of labor costs can thus shape a firm's pricing strategy and supply curve. For instance, in Sweden, where wages are set through coordinated pattern bargaining and typically cover two to three years, wages are relatively stable. This stability can lead to sticky input costs, particularly for labor-intensive products.[13] Heikkinen and Lundh (2020) provide evidence that stronger trade unions and collective bargaining agreements contributed to wage stickiness in Sweden compared to Finland during the Great Recession. If wage stickiness leads to more stable input costs, this could influence firms' pricing behavior.

To examine this, we use data on total personnel costs from annual balance sheets and adjust

[13]For more information on Sweden's collective wage bargaining system, see Björklund et al. (2019).

firms' real total sales (from IPI data) using the aggregate PPI index from Statistics Sweden. We classify firms into the top 25th percentile of unit labor costs and re-estimate Equation (2) using a dummy variable set to one for firms in this top percentile.

The results, presented in the lower left panel of Figure 7, suggest that firms with relatively low unit labor costs have a significantly steeper supply curve. The impulse responses shown in Figure A.22 in the Appendix indicate that these firms respond to demand shocks by increasing prices more significantly than firms with high labor costs. This finding implies that wage stickiness may influence the magnitude of supply elasticity for firms with high unit labor costs.[14]

Financial frictions

Finally, financial frictions can significantly influence firms' pricing strategies. The notion that capital market imperfections may impact pricing decisions has been explored since the work of Chevalier and Scharfstein (1996). More recently, Gilchrist et al. (2017) investigated how variations in firms' internal liquidity positions influenced their price-setting behavior during the financial crisis. Their findings revealed that liquidity-constrained firms substantially increased prices in 2008, while firms with ample internal liquidity significantly reduced prices. In the European context, Hristov et al. (2015) using German firm-level data and de Almeida (2015) employing industry-level producer prices in the Euro Area, also found that financially constrained firms were more prone to raise prices compared to their unconstrained counterparts.

Our annual balance sheet dataset includes information on firms' leverage, defined as the ratio of total long-term debt to total assets. We use this data to examine whether the supply elasticity differs between highly leveraged firms (above the 75th percentile in leverage distribution) and their financially unconstrained counterparts. The results, displayed in the lower right panel of Figure 7, align with existing literature, indicating that financially constrained firms exhibit higher supply elasticities. However, the difference in estimated elasticities between the two groups is not statistically significant. As illustrated in Figure A.23 in the Appendix, firms with high

[14]These findings should be interpreted cautiously due to low first-stage F statistics, as shown in Figure A.22.

leverage tend to charge higher prices following a demand shock, consistent with previous research. Nevertheless, the first-stage F-statistics suggest caution when interpreting the results for highly leveraged firms, as the instrument becomes notably weak for this group of firms.

6 Conclusion

Our study analyzes price and quantity adjustments in response to aggregate demand shocks using a unique monthly dataset of Swedish firms, combining PPI price data and IPI sales data. We identify demand shocks using global-demand shocks as instruments. The average price elasticity of supply is estimated around 0.35 but varies significantly depending on the economic context. It is higher during periods of low financial uncertainty and high inflation. Additionally, firm-specific factors such as exporting status and sales volatility significantly influence the supply elasticity, with lower elasticity observed for exporters and firms with high sales volatility.

These findings have important policy implications, suggesting that firms' responses to policy changes can vary significantly based on economic conditions and specific firm characteristics. Such variation may result in production misallocation and unequal profit distributions among firms. To address these disparities, theoretical models should be developed to account for this heterogeneity, offering tailored policy prescriptions that consider the diverse effects of demand-side interventions on different types of firms.

References

Anderson, T. W. and Rubin, H. (1949), 'Estimation of the parameters of a single equation in a complete system of stochastic equations', *The Annals of mathematical statistics* **20**(1), 46–63.

Armelius, H., Hull, I. and Köhler, H. S. (2017), 'The timing of uncertainty shocks in a small open economy', *Economics Letters* **155**, 31–34.

Arndt, S. and Enders, Z. (2023), 'The transmission of supply shocks in different inflation regimes'.

Bachmann, R., Born, B., Elstner, S. and Grimme, C. (2019), 'Time-varying business volatility and the price setting of firms', *Journal of Monetary Economics* **101**, 82–99.

Barnichon, R. and Mesters, G. (2021), 'The phillips multiplier', *Journal of Monetary Economics* **117**, 689–705.

Baumeister, C. and Hamilton, J. D. (2019), 'Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks', *American Economic Review* **109**(5), 1873–1910.

Björklund, M., Carlsson, M. and Nordström Skans, O. (2019), 'Fixed-wage contracts and monetary non-neutrality', *American Economic Journal: Macroeconomics* **11**, 171–92.

Blanco, A., Boar, C., Jones, C. J. and Midrigan, V. (2024), Non-linear inflation dynamics in menu cost economies, Technical report, National Bureau of Economic Research.

Boehm, C. E. and Pandalai-Nayar, N. (2022), 'Convex supply curves', *American Economic Review* **112**(12), 3941–69.

Bu, C., Rogers, J. and Wu, W. (2021), 'A unified measure of fed monetary policy shocks', *Journal of Monetary Economics* **118**, 331–349.

Bunn, P., Anayi, L. S., Bloom, N., Mizen, P., Thwaites, G. and Yotzov, I. (2022), Firming up price inflation, Technical report, National Bureau of Economic Research.

Buzzell, R. D., Gale, B. T. and Sultan, R. G. (1975), 'Market share-a key to profitability', *Harvard business review* **53**(1), 97–106.

Carvalho, C. and Nechio, F. (2016), 'Factor specificity and real rigidities', *Review of Economic Dynamics* **22**, 208–222.

Chevalier, J. A. and Scharfstein, D. S. (1994), 'Capital market imperfections and countercyclical markups: Theory and evidence'.

Chevalier, J. A. and Scharfstein, D. S. (1996), 'Capital-market imperfections and countercyclical markups: Theory and evidence', *The American Economic Review* **86**(4), 703–725.

Coibion, O. and Gorodnichenko, Y. (2015), 'Is the phillips curve alive and well after all? inflation expectations and the missing disinflation', *American Economic Journal: Macroeconomics* **7**(1), 197–232.

Comin, D. and Philippon, T. (2005), 'The rise in firm-level volatility: Causes and consequences', *NBER macroeconomics annual* **20**, 167–201.

de Almeida, L. A. (2015), 'Firms' balance sheets and sectoral inflation in the euro area during the financial crisis', *Economics Letters* **135**, 31–33.

Dedola, L., Kristoffersen, M. S. and Zullig, G. (2021), 'The extensive and intensive margin of price adjustment to cost shocks: Evidence from danish multiproduct firms', *Mimeo* .

Gagliardone, L., Gertler, M., Lenzu, S. and Tielens, J. (2023), 'Anatomy of the phillips curve: Micro evidence and macro implications', *NBER Working Paper* (31382).

Gilchrist, S., Schoenle, R., Sim, J. and Zakrajšek, E. (2017), 'Inflation dynamics during the financial crisis', *American Economic Review* **107**(3), 785–823.

Harding, M., Lindé, J. and Trabandt, M. (2023), 'Understanding post-covid inflation dynamics', *Journal of Monetary Economics* .

Heikkinen, S. and Lundh, C. (2020), 'Sticky swedes and flexible finns: manufacturing labour markets in finland and sweden during the great depression', *Scandinavian Economic History Review* **68**(2), 145–169.

Hristov, N., Menno, D., Balleer, A. et al. (2015), Financial market imperfections and the pricing decision of firms: Theory and evidence, *in* '2015 Meeting Papers', number 1173, Society for Economic Dynamics.

Jarociński, M. and Karadi, P. (2020), 'Deconstructing monetary policy surprises—the role of information shocks', *American Economic Journal: Macroeconomics* **12**, 1–43.

Keynes, J. M. (1939), 'Relative movements of real wages and output', *The Economic Journal* **49**(193), 34–51.

Klein, M., Strömberg, K. and Tysklind, O. (2024), 'Inflation dynamics in the high inflation period: insights from microdata', *Sveriges Riksbank Economic Commentary* **14**, 4 July.

Kumar, S., Gorodnichenko, Y. and Coibion, O. (2023), 'The effect of macroeconomic uncertainty on firm decisions', *Econometrica* **91**(4), 1297–1332.

Laséen, S. and Nilsson, C. (2024), How does the riksbank's monetary policy affect the swedish economy: does inflation rise when the policy rate is raised?, Technical report, Staff Memo Sveriges Riksbank.

Montiel-Olea, J. and Pflueger, C. (2013), 'A Robust Test for Weak Instruments', *Journal of Business and Economic Statistics* **31**(3), 358–369.

Nakamura, E. and Steinsson, J. (2010), 'Monetary non-neutrality in a multisector menu cost model', *The Quarterly journal of economics* **125**(3), 961–1013.

Pigou, A. C. (1927), 'The laws of diminishing and increasing cost', *The Economic Journal* **37**(146), 188–197.

Ramey, V. A. and Zubairy, S. (2018), 'Government Spending Multipliers in Good Times and in Bad: Evidence from US Historical Data', *Journal of Political Economy* **126**, 850–901.

Shea, J. (1993), 'Do Supply Curves Slope Up?', *The Quarterly Journal of Economics* **108**(1), 1–32.

Vavra, J. (2014), 'Inflation dynamics and time-varying volatility: New evidence and an ss interpretation', *The Quarterly Journal of Economics* **129**(1), 215–258.

A Appendix

A.1 Data

The firm-level data on prices and real output at the monthly frequency is assembled using information from four separate microdata sources, which are described in more detail below.

A.2 Sources

The data on firms' prices and output are obtained from the microdata underlying the official Swedish Producer and import price index (*Prisindex i producent- och importled*, PPI) and Industrial production index (*Industriproduktionsindex*, IPI), respectively. These datasets are maintained by Statistics Sweden. The PPI data include monthly product-level prices for a representative sample of products produced in the Swedish domestic market or produced abroad and imported to Sweden. Thus, the data contains both domestic, export and import producer prices. The unit of observation is the price of a product-level transaction, specifically referred to as a "product offering", which is a unique combination of a product sold by a particular firm. Firms that are selected from the sampling procedure are asked to report the price of a representative product they sell within a narrowly defined product code, given by the 8-digit Combined Nomenclature (CN) classification, and are required to respond by law. Our original PPI data covers the period January 1992 to September 2022 and includes roughly 1.75 million product-month observations.

The IPI data contains information on firms' total nominal net sales, broken down into domestic and export sales[15]. The data is based on a stratified sample of Swedish industrial firms above a certain *cut-off* (defined, within each industry, as the largest firms that together make up 95 percent of total sales) and are collected at the monthly frequency. Selected firms are required to

[15]Before 2015, the Swedish IPI used firm deliveries instead of net sales. With the switch to net sales, the IPI's methodology, including sampling design and estimation, was updated. These adjustments are included in the official IPI to prevent time-series breaks, and we follow Statistics Sweden's method in our data cleaning process (see Section A.3).

respond and are asked to report their monthly total net sales to domestic and foreign customers in thousands of Swedish Krona (SEK). Our original IPI data includes around 550,000 firm-month observations spanning between January 1998 and September 2022.

In order to aggregate the product-level PPI data to the firm level, as well as to construct a measure of firms' market shares (see details in Section A.3), we make use of information from a third dataset maintained by Statistics Sweden, the Production of Commodities and Industrial Services (*Industrins varuproduktion*, IVP) survey. The IVP data contains annual product-level information on delivered quantities and transaction prices, where products are defined according to the 8-digit CN code classification, and are available from 1997 up until 2020. The target population is total production value (i.e. delivered quantity times transaction price) per product within the Swedish industrial sector and, thus, the survey aims to provide information on how domestic industrial production is distributed across products. Only firms with at least 20 employees are considered for the survey and sampled firms, which are required to respond by law, are asked to allocate their annual production value over the products they sell. Our original IVP data contains around 175,000 product-year observations.

Lastly, we utilize annual balance sheet and income statement data obtained from the credit bureau Upplysningscentralen (UC), covering the population of Swedish corporations (*aktiebolag*). In particular, we draw from this data source information on firms' total assets, sales, personnel costs, long-term debt and number of employees. The original UC data are available between 1989 and 2020.

A.3 Dataset construction

As we aim to study the relationship between firms' real output and price-setting, our main dataset is a merge between the PPI price data and the IPI sales data. In order to aggregate the PPI data to the firm level, we furthermore make use of the IVP data. Lastly, we add on a number of variables constructed from the PPI, IVP and UC datasets to the merged IPI-PPI data, in

order to evaluate relevant heterogeneities in firm-level responses. The following section describes our data cleaning procedures for the various datasets as well as provides definitions and details regarding the main variables of interest in our analysis.

We perform several rounds of cleaning of the raw data. With regards to the PPI data, we drop a small number of missing, erroneous (negative) or duplicated price observations. Furthermore, we restrict the sample to products belonging to product groups B and C as defined by the Swedish Standard for Product Classification by Industry (SPIN), i.e. products sold within the industrial sector, since this is equivalent to the sample of firms present in the IPI data. In the baseline analysis, we only include the domestic part of the PPI, however, we also provide additional results focusing on export prices.

As described above, the unit of observation in the PPI data is product-firm-month. Given that the IPI data is at the firm level, we want to aggregate the PPI data and construct a firm-specific price measure representing the average price across a firm's products in each month. This aggregation is done in multiple steps. Firstly, we use the IVP data to construct annual product-level weights defined as $w_{p,i,s} = ProdV_{p,i,s-1} / \sum_p ProdV_{p,i,s-1}$, where $ProdV_{p,i,s}$ denotes the total production value of product p, sold by firm i in year s. In other words, the prices of products that contribute more to the total production value of a given firm will be attributed a higher weight in the firm-level price measure. Furthermore, to make sure that the price measure is representative of the prices of all products of a given firm, we compute the production value of all products observed in the PPI data relative to the firm's total production value in a given year, and require this fraction to be at least 50 percent to keep a particular firm-year in our sample. Once we have constructed the weights and imposed the above-mentioned restriction, we aggregate product-level prices to the firm level as a weighted arithmetic average. Although the PPI data is available since 1992 (and the IVP data since 1997), when using data prior to 2001 we cannot replicate well the official aggregate PPI series and for that reason we start our exercise in 2001.

Concerning the IPI data, we drop one firm which displays extreme outlier values and adjust a small number of observations such that the sum of domestic and export sales is always equal to total

sales, either by filling in missing values or by scaling total sales by the respective shares of domestic and export sales. Moreover, we account for a methodological change in Statistics Sweden's data collection procedure, which involves using three months of overlapping data at the time of the change to compute a quota representing the effect on each firm's reported deliveries/sales. Scaling the series by this quota then allows us to obtain coherent numbers throughout the sample period. In accordance with the price data, we keep only domestic sales in the baseline analysis, but also present results only including export sales. To get our real output measure, we deflate firms' monthly domestic (export) net sales by the domestic (export) part of the aggregate PPI for SPIN groups B and C, retrieved from Statistics Sweden's website. Lastly, since there is a high degree of volatility in monthly firm-level sales, we smooth the series by computing a centered three-months moving average.[16]

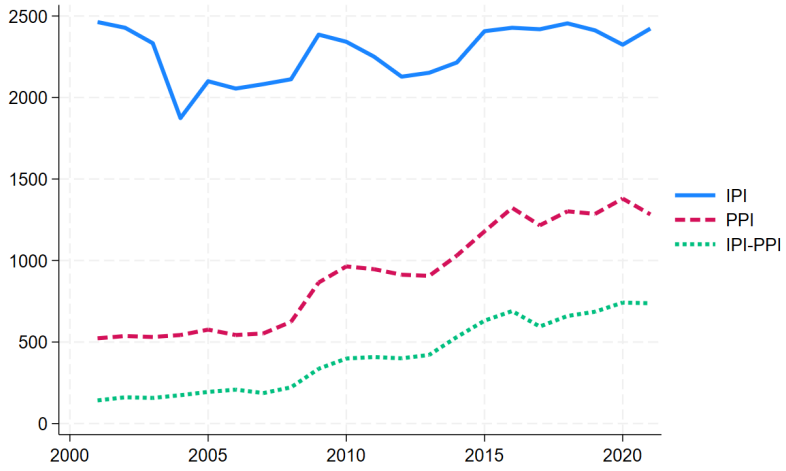
We assemble the final dataset by merging the monthly firm-level PPI price and IPI sales series, while at the same time merging additional variables constructed from the PPI, IVP and UC data. Specifically, we construct a measure of price-change frequency from the PPI data, defined as a product's total number of price changes within a year, and aggregate it to the firm level in the same way as the price measure. Moreover, we compute annual market shares as the share of IVP production value within 4-digit CN codes. In the case that a firm operates in multiple markets, the measure is aggregated to the firm level as a weighted arithmetic average, using the production value within each market as weights. We construct a measure of unit labor costs as the ratio between firms' total personnel costs (UC data) and real total sales (IPI data), where sales are deflated by the official aggregate PPI index. Finally, using the UC data, we define firm productivity and leverage as the ratio between annual total sales and number of employees, and total long-term debt and total assets, respectively.

[16]To make the IPI and PPI series comparable, we equivalently compute a three-months moving average for the firm-level price data.

A.4 Summary statistics

When assembling the merged IPI-PPI dataset, the final sample of firms is affected by two main bottlenecks. The first one stems from the fact that the firms in the PPI and IPI data are not entirely overlapping, which implies that a merge between these datasets will result in a loss of some fraction of firms each month. Moreover, in order to aggregate the PPI data to the firm-level, we impose a restriction requiring the observed PPI products to account for at least half of the firm's total production value each year, implying a loss of an additional number of firms. To show how these restrictions affect our sample, Figure A.1 plots the total number of firms present each year in the PPI, IPI and merged IPI-PPI datasets, respectively. As shown, data cleaning significantly reduces the sample size, in particular, in the first ten years of the sample[17].

Figure A.1: Total Number of Firms



Notes: The figure displays the total number of firms present each year in three separate datasets: (i) the IPI data, (ii) the domestic part of the PPI data, restricting the sample to products belonging to SPIN groups B and C, and (iii) the merged IPI-PPI data that we use for our analysis.

Given the large change in the sample size, to compare the characteristics of the firms included in the PPI, IPI and merged IPI-PPI datasets, Table A.1 presents summary statistics for selected

[17]To investigate the robustness of our results to the limited availability of data at the beginning of the sample, we repeat our analysis starting the sample in 2010 in the Appendix (see Figure A.4). Results are not sensitive to the sample size.

Table A.1: Summary Statistics, Balance Sheet Items

	IPI	PPI	IPI-PPI	IPI	PPI	IPI-PPI
	Assets			Sales		
Mean	18.09	19.13	19.57	18.58	19.59	20.01
Standard deviation	1.85	1.69	1.58	1.73	1.56	1.43
25th percentile	16.84	17.98	18.52	17.38	18.55	19.05
Median	17.99	18.95	19.40	18.54	19.44	19.87
75th percentile	19.21	20.12	20.45	19.66	20.53	20.82
	Employment			Productivity		
Mean	4.06	4.76	5.10	14.56	14.85	14.92
Standard deviation	1.38	1.29	1.19	0.72	0.73	0.72
25th percentile	3.09	3.85	4.26	14.10	14.39	14.48
Median	3.99	4.62	5.00	14.50	14.77	14.85
75th percentile	4.93	5.56	5.87	14.97	15.24	15.31

Notes: The table presents summary statistics for selected balance sheet items drawn from the UC data. The variables included are the logarithm of total assets, total sales, number of employees and productivity (defined as the ratio between total sales and employees). The three samples considered are (i) the full IPI data, (ii) the domestic part of the PPI data, restricting the sample to products belonging to SPIN groups B and C, and (iii) the merged IPI-PPI data that we use for our analysis. All samples cover the period 2001-2021.

balance sheet items for these three different samples. The IPI-PPI sample appears to be slightly biased towards larger and more productive firms. This is to some extent expected given that the IVP data (which are needed to construct the merged IPI-PPI data) excludes all firms with less than 20 employees. In spite of the differences highlighted, selected firms are not statistically different for all the characteristics we report in Table A.1 in the three samples.

Next, we present summary statistics for distinct firm features constructed from either the PPI or the IVP data. Specifically, we consider firms' average price-change frequency, market share and number of products (as defined by 8-digit CN codes). For each variable, the left column in Table A.2 displays the stated statistic when including the sample of firms from the full PPI or IVP data (depending on which data source the variable is constructed from), while the right column restricts the sample to our merged IPI-PPI data. As can be seen, the firms in our sample are in general comparable to those in the full PPI or IVP samples. Our matched dataset displays a slightly higher price change frequency, however the difference is not statistically significant. Prices change on average more than five times per year in our constructed sample, while prices in

Table A.2: Summary Statistics, Price and Sales Data

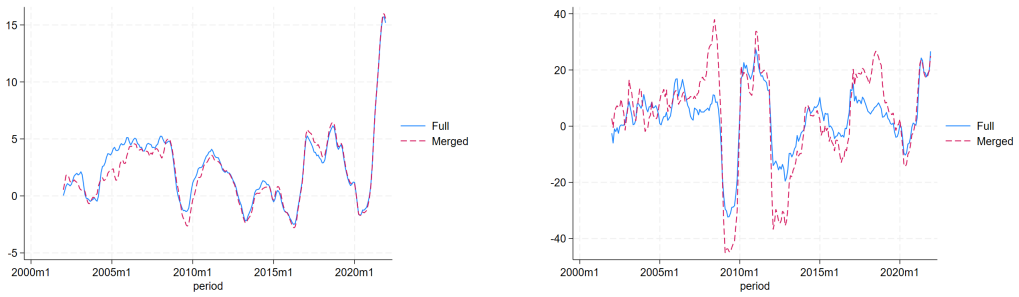
	PPI/IVP	IPI-PPI	PPI/IVP	IPI-PPI	PPI/IVP	IPI-PPI
	Price-change frequency		Market Share		Number of products	
Mean	4.84	5.19	0.16	0.23	3.47	3.67
Standard deviation	4.65	4.71	0.24	0.28	5.68	5.82
25th percentile	1.00	1.00	0.01	0.03	1.00	1.00
Median	3.00	3.00	0.04	0.10	2.00	2.00
75th percentile	10.00	11.00	0.18	0.34	3.00	4.00

Notes: The table presents summary statistics for firm-level variables constructed from the PPI or IVP data. We include the price-change frequency defined by the (weighted) average of total number of price changes within a year, the market share constructed as the firm's share of production value within 4-digit CN codes, and their average number of products as given by 8-digit CN codes. The market share and number of products variables are constructed from the IVP data, while the price-change frequency variable is constructed from the PPI data. The samples considered are (i) the full IVP data or the domestic part of the PPI data (restricting the sample to products belonging to SPIN groups B and C) depending on the dataset used to construct the variable, and (ii) the merged IPI-PPI data that we use for our analysis. All samples cover the period 2001-2021.

the unrestricted PPI data change slightly less frequently. Regarding the market share the merged IPI-PPI data involve on average firms with higher market shares than the unrestricted sample in the IVP data set. Again differences are not statistically significant but it is obvious that the distribution of the restricted sample we consider lies above the distribution of the unrestricted IVP firms. Finally, firms in the restricted sample do not significantly differ with firms in the unrestricted IVP sample regarding the number of products they sell. On average in both samples firms sell approximately 3.5 goods and the median is two goods per firm. The firms in the restricted sample seem to sell marginally more goods and this is because the right tale of their distribution is more skewed.

Lastly, to further evaluate the representativeness of the firms left in our merged data set, we compute the average monthly year-on-year percentage change in prices and net sales across all firms in the merged IPI-PPI and full IPI/PPI data, respectively. The numbers are displayed in Figure A.2. As shown, the aggregate dynamics in the merged dataset follows closely the dynamics when including the full sample of firms. In particular, for the PPI, apart from the first years of the sample, the comovements between prices in the two series is very high. Indeed, the correlation coefficient between the aggregate series based on the full and merged samples equals

Figure A.2: Aggregate Series



(a) PPI (b) IPI

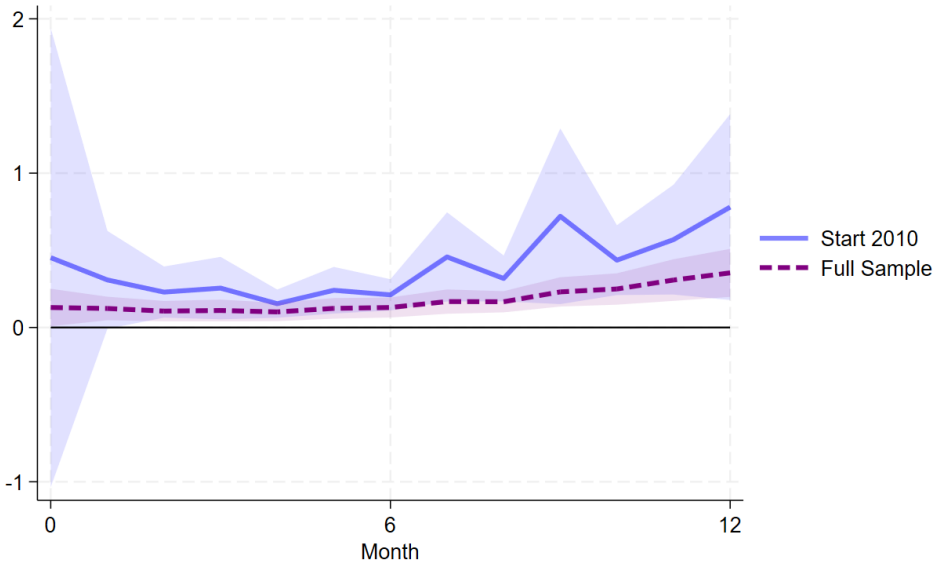
Notes: The figure plots year-on-year percentage changes in aggregate (a) PPI prices and (b) IPI net sales, when considering the full samples and our merged sample of firms separately. The aggregate PPI series comprise products belonging to SPIN groups B and C and are computed as a weighted arithmetic average, applying the product-specific weights used in the construction of the official index. The aggregate IPI series are computed as an arithmetic average of total net sales across all firms included in the samples. Both the PPI and IPI series are restricted to domestic sales/prices and are smoothed by applying a centered three-month moving average.

0.9755. When looking at net sales data, the full sample and merged data share the same trends but exhibit some deviations, reflected in a lower correlation coefficient between the aggregate series based on the full and merged samples that equals 0.8855.

Taken together, the statistics presented in this section suggest that the bottlenecks present in our data assembly should have limited impact on the bias of the estimates we present next.

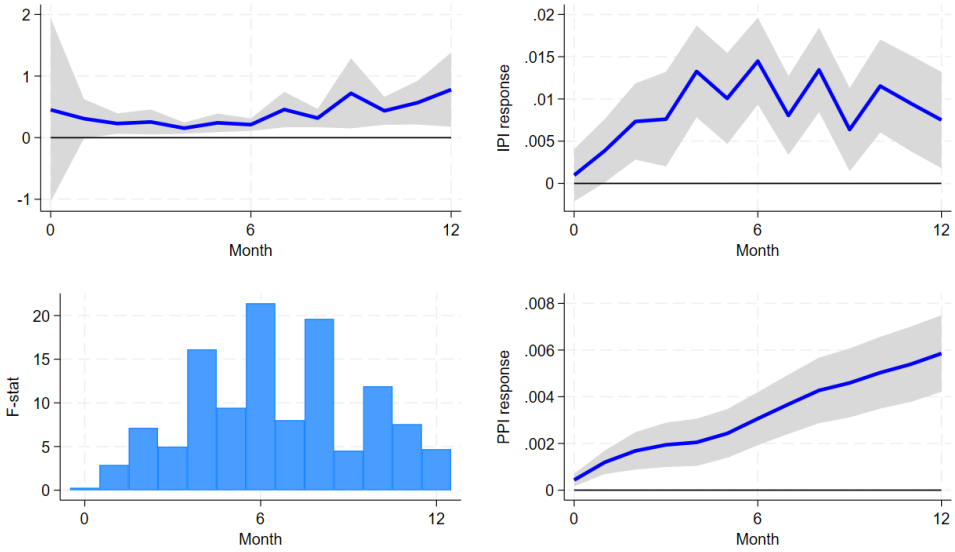
A.5 Additional results

Figure A.3: Restricted sample 2010-2021



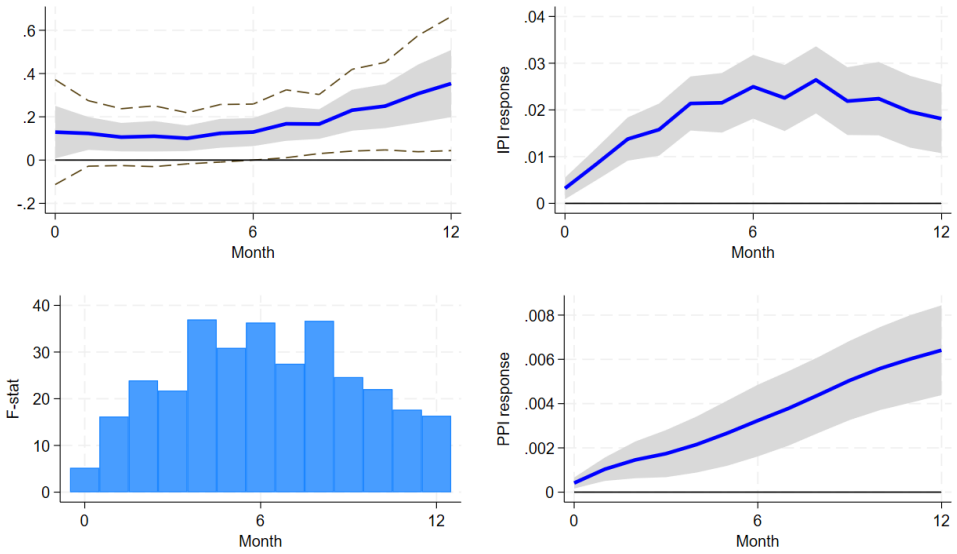
Notes: Estimated average supply curve using Baumeister and Hamilton (2019) global demand shocks as instruments (continuous line). The dotted lines depict the estimated slope when the start of the sample is 2010m1 instead of 2001m1. Standard errors are clustered at the firm level.

Figure A.4: Restricted sample 2010-2021



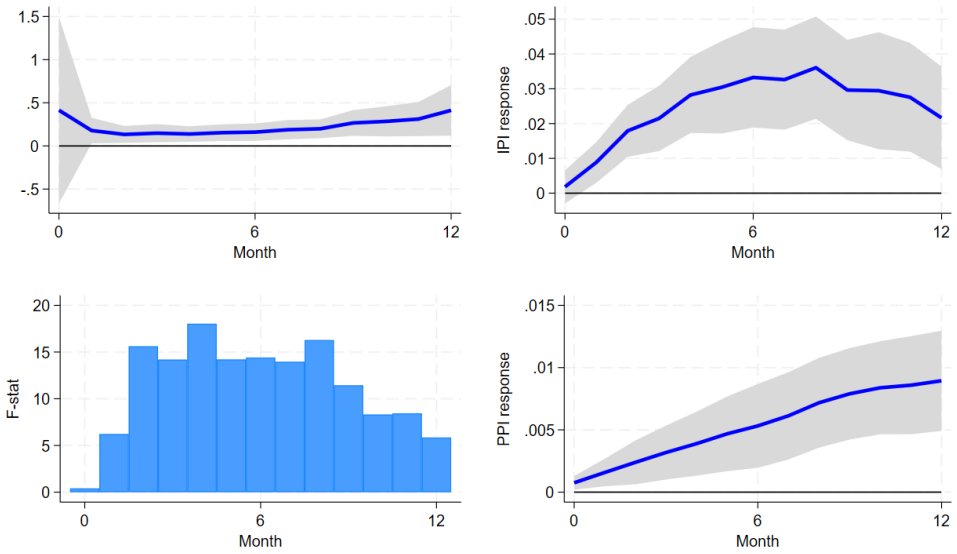
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. We cluster standard errors at the firm level. The sample is 2010m1-2021m12.

Figure A.5: Accounting for weak instrument (Anderson and Rubin (1949) confidence bands)



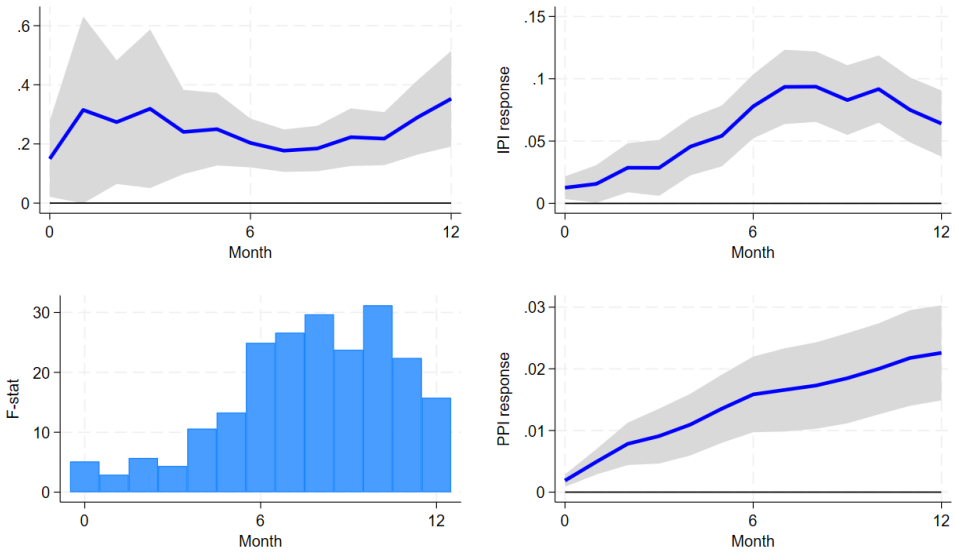
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence bands when we cluster standard errors at the firm level while dotted lines correspond to 90% confidence bands constructed using weak instrument robust methods. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. The sample is 2001m1-2021m12.

Figure A.6: Controlling for Changes in Import Prices



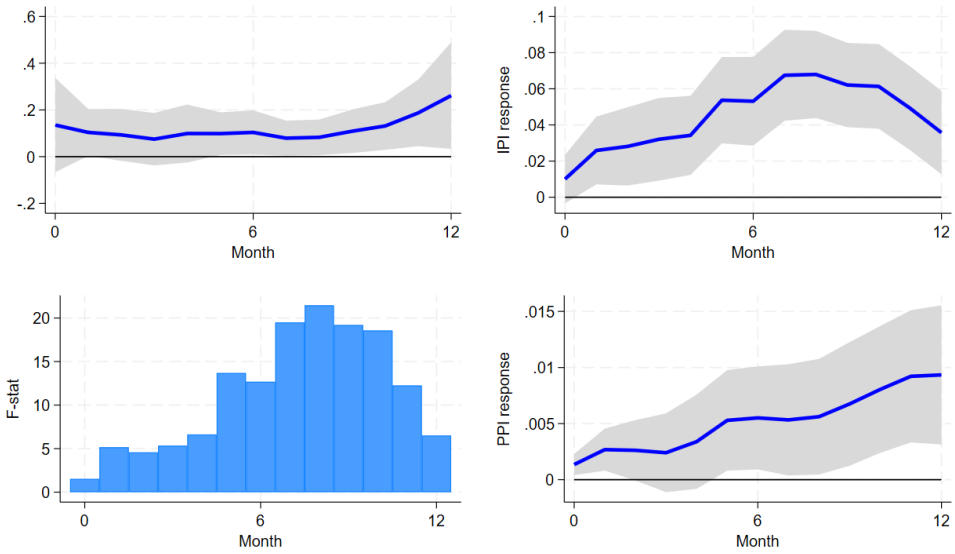
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. We cluster standard errors at the firm level. The sample is 2001m1-2021m12 and we control for six lags and the contemporaneous value of import price inflation in the baseline regression (1).

Figure A.7: Using the ECB monetary policy shocks as instruments for changes in demand



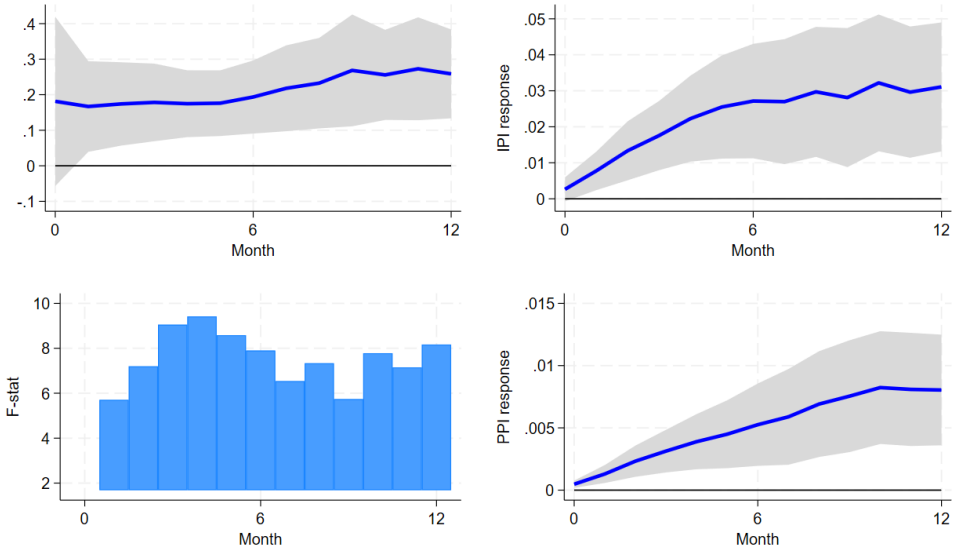
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12 when we use the ECB monetary policy shocks as instruments for changes in firms' demand. Shaded areas correspond to the 90% confidence region. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. We cluster standard errors at the firm level. The sample is 2001m1-2021m12 and we control for the contemporaneous EUR/SEK exchange rate, using the monthly series from the Riksbank's website that takes the average exchange rate over the month.

Figure A.8: Riksbank shock



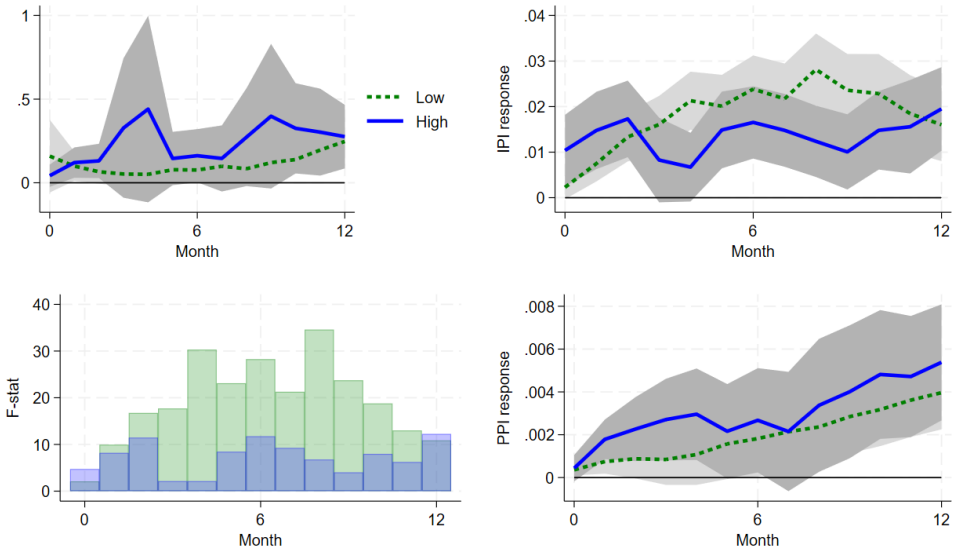
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12 when we use the Riksbank monetary policy shocks as instruments for changes in firms' demand. Shaded areas correspond to the 90% confidence region. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. We cluster standard errors at the firm level. The sample is 2001m1-2021m12 and we control for lags of Swedish unemployment and change in IMF commodity price index (as described earlier in the text).

Figure A.9: Estimates using aggregate data



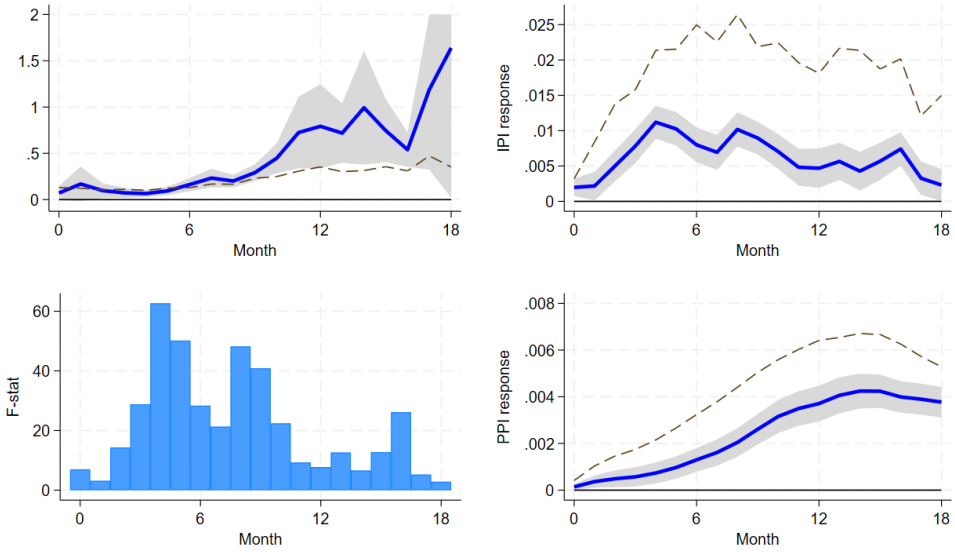
Notes: The top left panel presents estimates for the average slope of the firm-supply curve when using aggregate instead of firm level data for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. We use Newey-West standard errors. The sample is 2001m1-2021m12.

Figure A.10: State-dependency: Capacity utilization



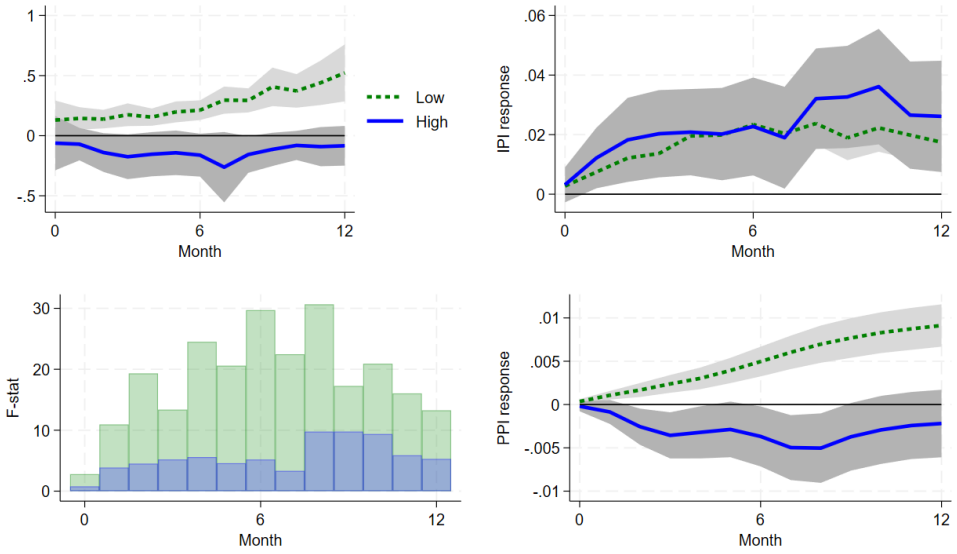
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. Blue continuous line presents estimates for the periods for which capacity utilization is above the 75 percentile of its value in the sample and green lines periods below this level. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. Blue bars correspond to estimates in the high utilization regime and green in the low utilization regime. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. We cluster standard errors at the firm level. The sample is 2001m1-2021m12. Again blue continuous lines correspond to the high utilization regime estimates and green dotted lines to the low utilization regime.

Figure A.11: Further Extensions: Including recent Surge in Inflation



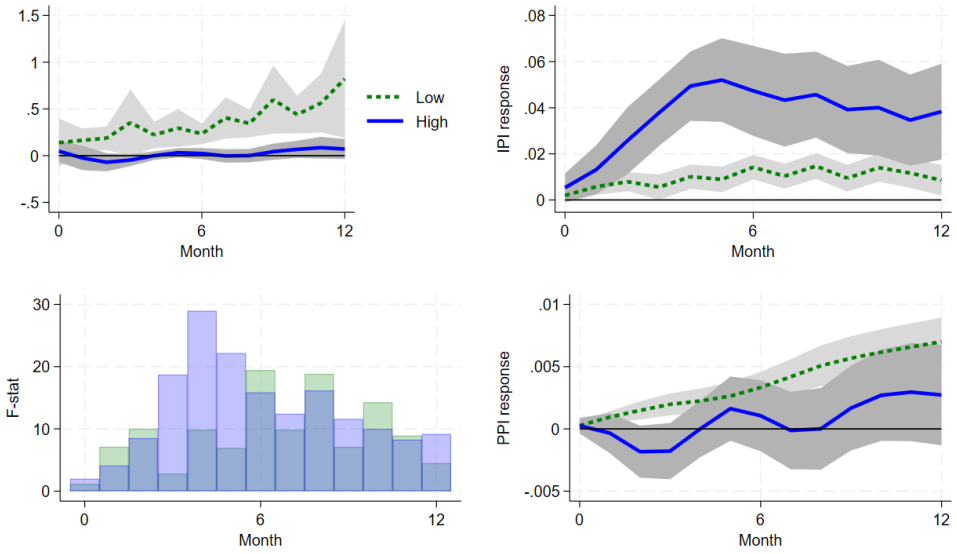
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=18. Shaded areas correspond to the 90% confidence region. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. We cluster standard errors at the firm level. The sample is 2001m1-2022m9. Dotted lines are baseline estimates.

Figure A.12: State-dependency: Uncertainty (EU STOXX Volatility)



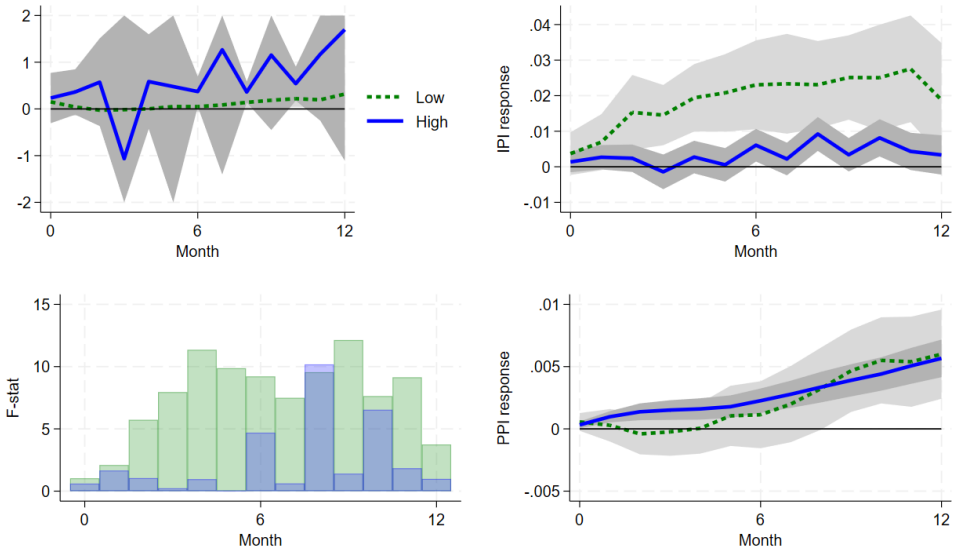
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. Green dotted lines characterize months for which the EU STOXX is above its 75 percentile and blues continuous lines months for which the EU STOXX is below the 75 percentile in the sample. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression 1 for the same horizon range. Blue bars correspond to periods of high and green bars to periods of low uncertainty. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. Again blue continuous lines correspond to periods of high and green dotted lines to periods of low uncertainty, respectively. We cluster standard errors at the firm level. The sample is 2001m1-2021m12.

Figure A.13: State-dependency: Uncertainty (VIX Volatility)



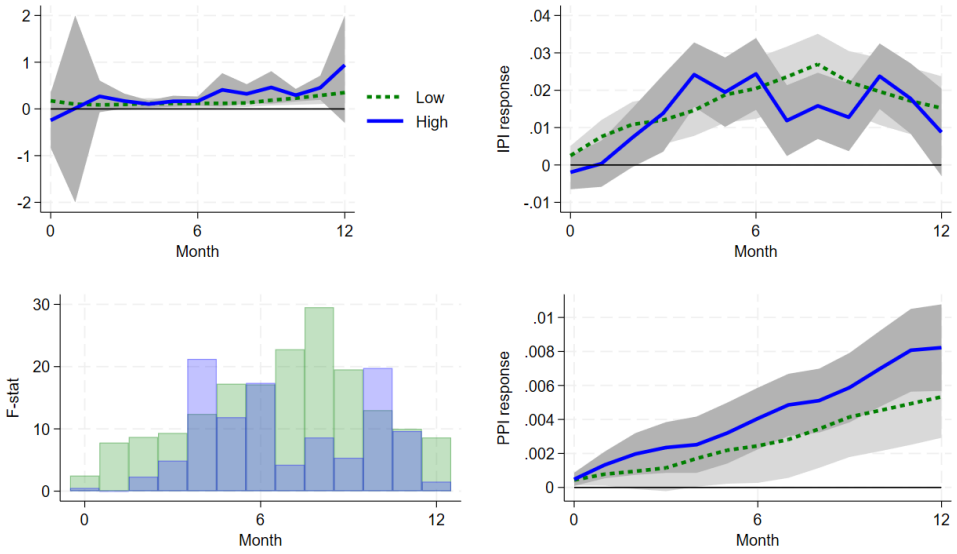
Notes:The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. Green dotted lines characterize months for which the VIX is above its 75 percentile and blues continuous lines months for which the VIX is below the 75 percentile in the sample. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression 1 for the same horizon range. Blue bars correspond to periods of high and green bars to periods of low uncertainty. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. Again blue continuous lines correspond to periods of high and green dotted lines to periods of low uncertainty, respectively. We cluster standard errors at the firm level. The sample is 2001m1-2021m12.

Figure A.14: State-dependency: Macroeconomic Uncertainty



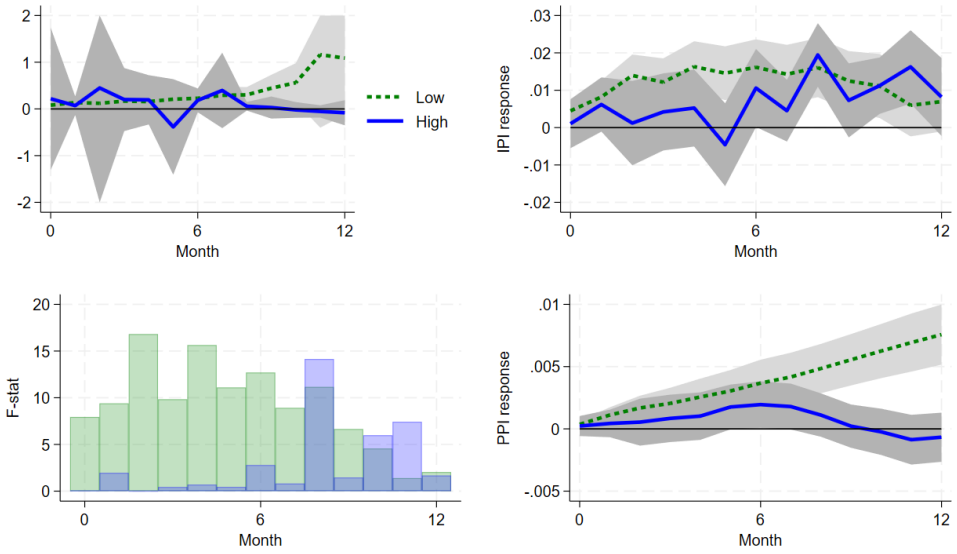
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. Blue continuous lines characterize months during the great financial crisis, the EU sovereign debt crisis and the COVID crisis and green dotted lines the rest of the periods. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. Blue bars correspond to periods of high and green bars to periods of low macro uncertainty. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. Again blue continuous lines correspond to periods of high and green dotted lines to periods of low macro uncertainty, respectively. We cluster standard errors at the firm level. The sample is 2001m1-2021m12.

Figure A.15: State-dependency: EPU Uncertainty



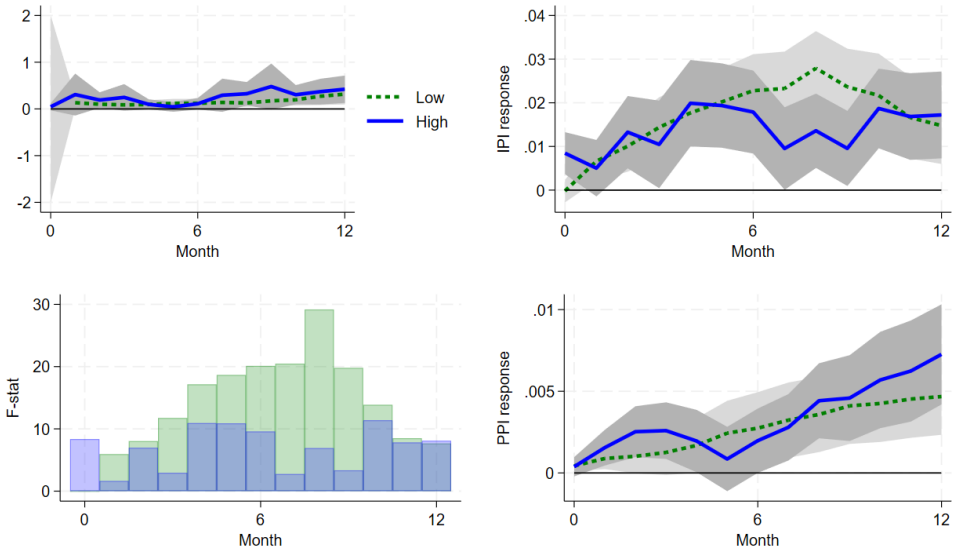
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. Green dotted lines characterize months for which the EPU index is above its 75 percentile and blues continuous lines months for which the EPU index is below the 75 percentile in the sample. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. Blue bars correspond to periods of high and green bars to periods of low EPU uncertainty. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. Again blue continuous lines correspond to periods of high and green dotted lines to periods of low EPU uncertainty, respectively. We cluster standard errors at the firm level. The sample is 2001m1-2021m12.

Figure A.16: State-dependency: Recessions vs. Expansions



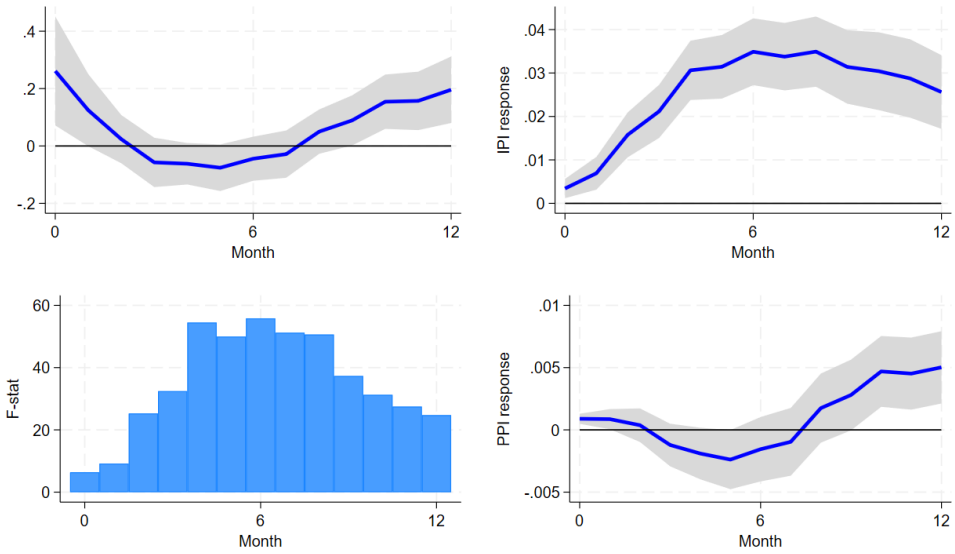
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. Green dotted lines characterize months for which the unemployment rate is below its 75 percentile and blues continuous lines months for which the unemployment rate is below the 75 percentile in the sample. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. Blue bars correspond to periods of high and green bars to periods of low unemployment. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. Again blue continuous lines correspond to periods of high and green dotted lines to periods of low unemployment, respectively. We cluster standard errors at the firm level. The sample is 2001m1-2021m12.

Figure A.17: State-dependency: Tight vs. Loose Labor market



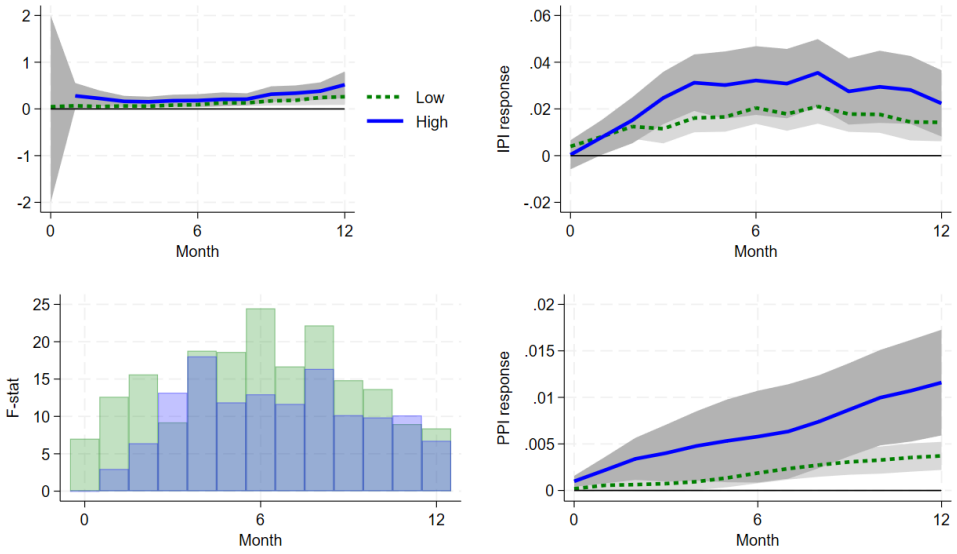
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. Green dotted lines characterize months for which the vacancy rate is below its 75 percentile and blue continuous lines months for which the vacancy rate is below the 75 percentile in the sample. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. Blue bars correspond to periods of high and green bars to periods of low vacancy rate. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. Again blue continuous lines correspond to periods of high and green dotted lines to periods of low vacancy rate, respectively. We cluster standard errors at the firm level. The sample is 2001m1-2021m12.

Figure A.18: Firm characteristics: Export Supply Curve



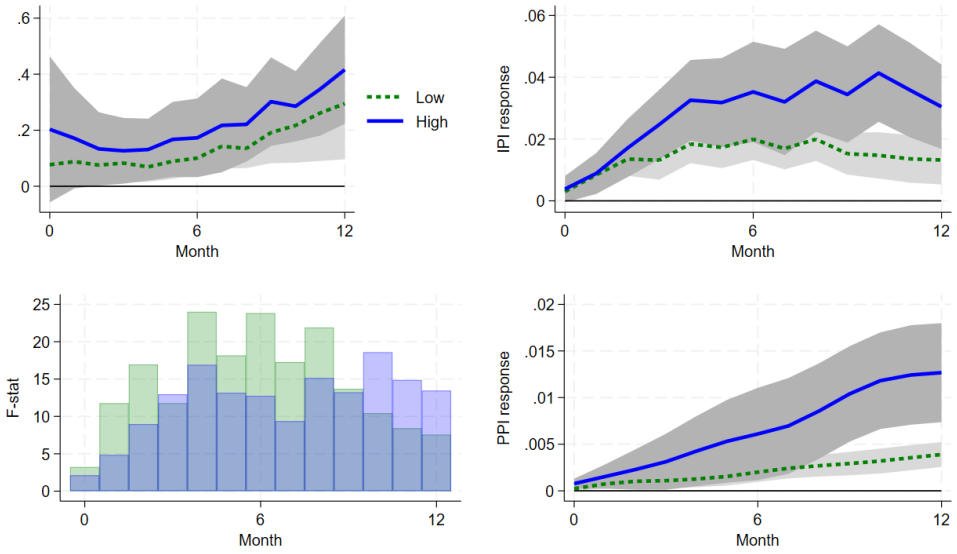
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for export prices for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. The top and bottom right panels present impulse responses for average export price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. We cluster standard errors at the firm level. The sample is 2001m1-2021m12.

Figure A.19: Firm characteristics: Market Share



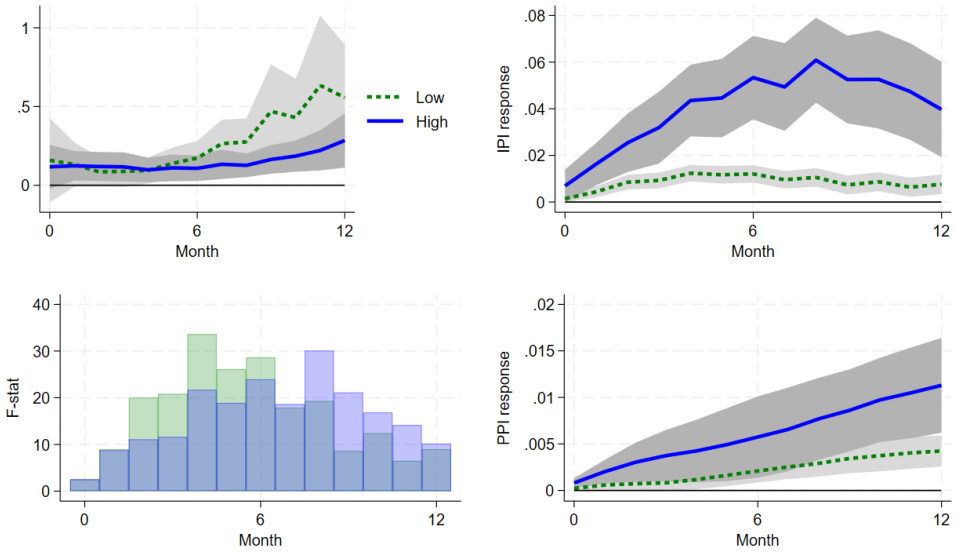
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. Green dotted lines characterize firms with market share below 75 percentile in the firms distribution and blues continuous lines firms above the 75 percentile in the sample. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. Blue bars correspond to the sample with high and green bars to the sample with low market shares. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. Again blue continuous lines correspond to sample of high and green dotted lines the sample with low market share, respectively. We cluster standard errors at the firm level. The sample is 2001m1-2021m12.

Figure A.20: Firm characteristics: Productivity



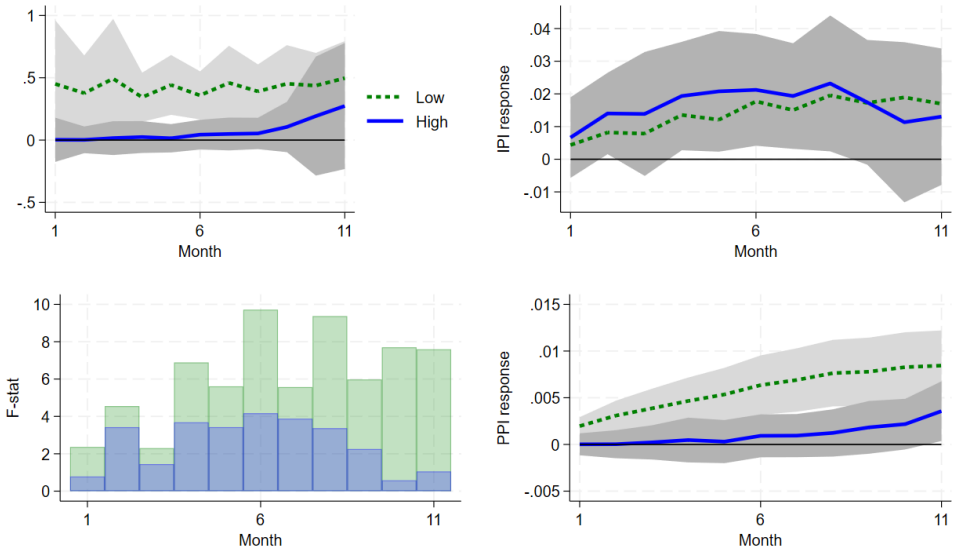
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. Green dotted lines characterize firms with productivity below 75 percentile in the firms distribution and blues continuous lines firms above the 75 percentile in the sample. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. Blue bars correspond to the sample with high and green bars to the sample with low productivity firms. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. Again blue continuous lines correspond to sample of high and green dotted lines the sample with low productivity firms, respectively. We cluster standard errors at the firm level. The sample is 2001m1-2021m12.

Figure A.21: Firm characteristics: Uncertainty, cross-sectional volatility in firm sales



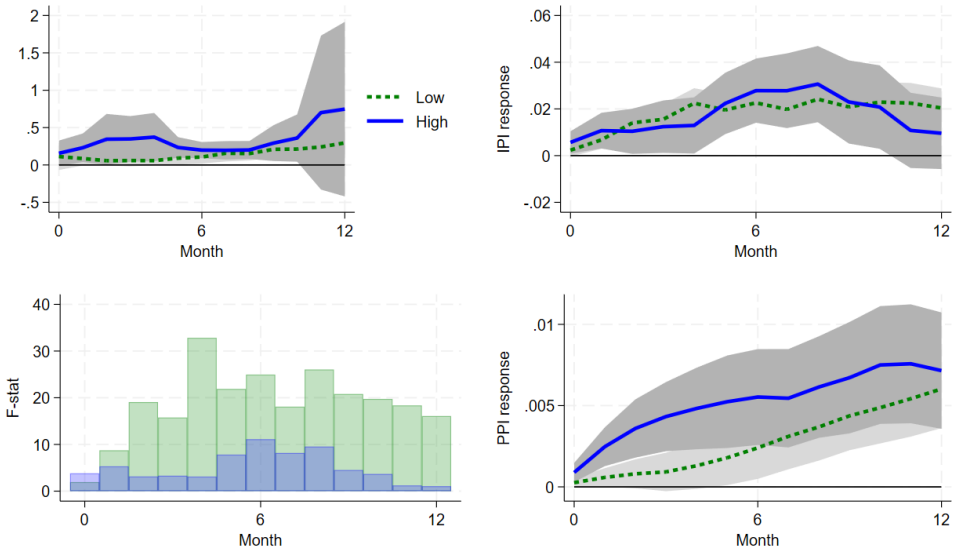
Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. Green dotted lines characterize firms with standard deviation of sales volatility below 75 percentile in the firm distribution and blues continuous lines firms above the 75 percentile in the sample. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. Blue bars correspond to the sample with high and green bars to the sample of firms with low volatility, respectively. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. Again blue continuous lines correspond to sample of high and green dotted lines the sample with firms with low sales volatility, respectively. We cluster standard errors at the firm level. The sample is 2001m1-2021m12.

Figure A.22: Firm characteristics: Unit labor cost



Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. Green dotted lines characterize firms with ULC below 75 percentile in the firms distribution and blues continuous lines firms above the 75 percentile in the sample. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. Blue bars correspond to the sample with high and green bars to the sample of firms with low ULC. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. Again blue continuous lines correspond to the sample of high and green dotted lines the sample with low ULC firms, respectively. We cluster standard errors at the firm level. The sample is 2001m1-2021m12.

Figure A.23: Firms characteristics: Leverage



Notes: The top left panel presents estimates for the average slope of the firm-supply curve for horizons h=0 till h=12. Shaded areas correspond to the 90% confidence region. Green dotted lines characterize firms with leverage below 75 percentile in the firms distribution and blues continuous lines firms above the 75 percentile in the sample. The bottom left panel depicts the (Montiel-Olea and Pflueger (2013)) F-statistics from the first stage of the instrumental variable regression (1) for the same horizon range. Blue bars correspond to the sample with high and green bars to the sample with firms with low leverage, respectively. The top and bottom right panels present impulse responses for average price and sales growth rates estimated from OLS regressions of price inflation and sales growth to an external demand shock and 90% confidence intervals. Again blue continuous lines correspond to sample of high and green dotted lines the sample with firms with low leverage, respectively. We cluster standard errors at the firm level. The sample is 2001m1-2021m12.