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Price Pass-Through Along the Supply Chain: Evidence from PPI and CPI Microdata*

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Abstract

We examine the pass-through from producer to consumer prices, using product-group data derived from the microdata underlying the official Swedish PPI and CPI indices. We find a robust pass-through, in line with theoretical models emphasizing production inter-linkages between sectors. The results also display important heterogeneity in pricing behavior both along the supply chain, as well as across product groups. That is, upstream pricing seems much more rigid than downstream pricing in the supply chain and the pass-through across CPI products varies substantially with price-change frequencies. The recent COVID- and high-inflation periods do not change the main results.

JEL classification: E30, E31, E32.

Keywords: Price pass-through, consumer and producer prices, microdata.

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1 Introduction

The most recent surge in inflation rates in many industrialised countries has led to an increased interest in understanding price-setting behavior. A key metric for investigating inflation dynamics is the price pass-through along the supply chain, i.e. by how much a change in producer prices transmit into changes in consumer prices. The theoretical literature typically highlights the important role of a significant pass-through from producer to consumer prices in economies with strong inter-linkages between sectors where upstream pricing shapes downstream cost (Baqaee and Farhi, 2022; Acemoglu et al., 2012). In this paper, we use a novel granular price data set and provide robust evidence of a strong price pass-through.

In particular, we provide new empirical evidence on the pass-through from producer to consumer prices, utilizing product-level data comprising all of the price observations underlying the official Swedish producer and import price index (PPI) and consumer price index (CPI). Importantly, we establish a link between products in the PPI and CPI by merging related product groups observed in both price indices. Examples of product groups included in both the PPI and CPI are food, furniture and fuels for transportation. This merge enables us to investigate the price pass-through at the very granular level, which offers several important advantages compared to estimates at the aggregate level. First, organizing the data in comparable product groups solves any issues with differences in the composition of the two aggregate indices, as emphasized by e.g. Clark (1995) when discussing reasons that would weaken the link between aggregate PPI and CPI indices. Secondly, with group-level data it is possible to control for any general equilibrium feedback effects that influence the interpretation of a regression of one aggregate price index on another. Third, the large cross-sectional variation of our micro price data should reduce estimation uncertainty on the relation between producer and consumer prices. Finally, pooling the data might mask important heterogeneity across individual product groups. We indeed show that the price-change frequency across product groups significantly influences the price pass-through. Our micro price data set, which covers the period from January 2010 to September 2022, further allows for an in-depth analysis on the pass-through during the recent COVID and high-inflation episodes.

To evaluate the price pass-through, we estimate local projections (Jordà, 2005) relating cumulated changes in consumer prices to cumulated changes in producer prices. Our baseline model is set up to trace the dynamic group-level response of consumer prices to a shock to producer prices. In particular, throughout we control for aggregate shocks common to both consumer and producer prices and past innovations to producer prices by including current and lagged values of the aggregate CPI as well as lags of producer prices at the group level, respectively.

Our baseline model estimates a significant, quick and constant price pass-through from producer to consumer prices, indicating that downstream pricing behavior in the economy does not add much to the dynamics of prices, speaking in favor of a flexible- or menu-cost model interpretation of consumer-side pricing. An increase in producer prices by 1 percent leads to an increase in consumer prices by about 0.25 percent within the same month. Thus, at the very short horizon, one fourth of the change in producer prices is transmitted into consumer prices. After two months, consumer prices are up by around 0.35 percent and the pass-through approximately stays at this level for the duration of the period of elevated producer prices. Given the large cross-sectional variation in the data, the estimated price pass-through is relatively precise with tight confidence bands up to 12-months out.

To account for potential endogeneity concerns due to strategic interaction between producer- and consumer pricing at the group level, and thus ensure the direction of causation of our pass-through estimates, we also rely on an external instrument for exogenous changes in producer prices. To this end, we construct a group-level instrument representing the weighted unit labor cost (ULC) for the producing firms, which is achieved by merging our micro price data with firm-level sales data underlying the official Swedish industrial production index and administrative balance sheet information. In a large class of macroeconomic models, ULC is a measure of marginal cost, and as argued in Carlsson and Skans (2012), can be used to isolate exogenous changes in producer prices conditional on aggregate controls. The first-stage regression shows a prolonged period of increasing producer prices in response to a rise in contemporaneous ULC which is well in line with significant Calvo-style nominal rigidities in the producer side of the economy and allows us to estimate the pass-through up to 24-months out with precision. Moreover, at horizons larger than three months, the F-statistic is well above the critical threshold, suggesting that weak instruments are unlikely to be a concern for our analysis, especially at the medium run. Overall, the estimated pass-through when using the ULC IV strategy is similar to our baseline approach, indicating that that there are no important feedback effects from consumer pricing to producer pricing in the supply chain.

Our findings further reveal strong heterogeneity across product groups. In particular, we find that the price-change frequency in CPI groups significantly influences the price pass-through. For groups with a high price-change frequency, like fuels for transportation or typical food items, the pass-through is immediate reaching its peak already after two months. In stark contrast, the pass-through is much more sluggish for product groups with a low price-change frequency, such as motor cycles or durables. While the immediate and constant adjustment for the high-frequency groups is well in line with the predictions of a flexible- or menu-cost pricing model, the prolonged gradual adjustment for the low-frequency groups better matches the predictions of a standard Calvo-pricing model. Importantly, by relying on granular data we are able to detect such significant heterogeneity whereas pooled analyses at the aggregate level mask important non-linearities.

All in all, the pass-through results above points to important differences in the pricing behavior, both along the supply chain and across product groups. This finding thus caution against drawing inference on the overall degree of price stickiness and its implications for e.g. the welfare cost of inflation from a too narrow data window.

The most recent episode does not significantly influence our main results. When dropping either the COVID period (January 2020 and onwards) or the high-inflation period (April 2021 and onwards), the estimated price pass-through is remarkably similar to our baseline estimates. This indicates that how changes in producer prices transmit into changes in consumer prices is relatively stable across time and did not significantly change in the most recent past.

The remainder of the paper is structured as follows. Section 2 describes the different data sources and in particular how we construct a link between related product groups in the PPI and CPI. Our empirical specification is discussed in Section 3. Section 4 presents our empirical findings. Finally, Section 5 concludes.

2 Data

The variables used in the analysis are constructed from five separate microdata sets. To begin with, we use monthly product-level price data comprising all individual products underlying the official Swedish PPI and CPI indices. The PPI data covers the period January 1992 to September 2022, while the CPI data is available only from January 2010. Moreover, we use annual product-level data on prices and delivered quantities drawn from the Production of Commodities and Industrial Services (IVP) survey, as well as the monthly firm-level sales data underlying the official Swedish Industrial Production Index (IPI). The IVP and IPI data are based on stratified samples of firms within the Swedish industrial sector, and are available from 1997 and 1998, respectively. The four above-mentioned data sets are maintained by Statistics Sweden (SCB). Lastly, we use annual balance sheet and income statement data on the population of Swedish corporations (*aktiebolag*), available from 1989 and obtained from the credit bureau Upplysningscentralen (UC).

In order to investigate the pass-through from producer to consumer prices at the micro level, we have to establish a link between related products in the PPI and CPI data. Product groups are defined differently in the PPI and CPI. In the former according to the Swedish Standard for Product Classification by Industry (*Standard för Svensk Produktindelning efter Näringsgren*, SPIN), and in the latter as subcategories to the Classification of Individual Consumption According to Purpose (COICOP). To construct a link between these different product-classification standards, we utilize the fact that the first four digits of the SPIN codes are equivalent to the Statistical Classification of Products by Activity (CPA), which, in turn, can be mapped to COICOP codes using correspondence tables available at Eurostat.[1] The matched PPI-CPI data set is then constructed by computing the weighted arithmetic average producer- and consumer price of all individual products within each COICOP code, using the same product-specific annual weights employed in the construction of the official PPI and CPI indices.[2] Table A1 in the Appendix provides the complete list of CPA codes which we are able to map to a COICOP code that is included in the CPI data. Before aggregation, we filter out a small number of individual price observations indicating negative prices as well as duplicated products. With regards to the PPI data, we restrict the sample to products within the industrial sector (SPIN groups B and C) sold at the Swedish domestic market.[3] This is to make the ULC measure, which we construct using data on a sample of firms within the Swedish industrial sector and is discussed more in detail below, relevant as an instrument in our analysis. In addition, we drop COICOP codes referring to alcohol products given that Sweden has a state-owned monopoly for all alcoholic beverages exceeding 3.5 percent of alcohol. The final monthly data set includes 5,142 observations across 34 separate COICOP product groups, comprising of 48 percent on average of the total weight in the CPI, spanning between January 2010 and September 2022.

Our measure of ULC for the producing firms, which will be used as an instrument in the empirical approach outlined below, is constructed in several different steps. We define ULC as the ratio between firms' annual personnel costs and monthly real total sales, where total sales are deflated by a monthly firm-specific price index. Personnel costs and total sales are drawn from the UC and IPI data, respectively. The firm-specific price index is constructed by combining the PPI and IVP data. In particular, we compute the weighted average monthly price of each firm's products, where the annual weight represents a product's contribution to the total production value (price times delivered quantity) of the firm.[4] To aggregate firm-level ULC to the COICOP level, we

[1] The tables are available at https://ec.europa.eu/eurostat/ramon. Specifically, we use the mapping between COICOP version 1999 and CPA version 2008.

[2] In the construction of the official Swedish CPI, prices in certain product groups are aggregated as a weighted geometric average. Since we aim to make the PPI and CPI prices as comparable as possible, we choose to aggregate solely applying arithmetic averages.

[3] Note that SPIN groups B and C comprise about 93 percent of all price observations in our PPI data.

[4] Since the sample of firms in our sales and price data are not entirely overlapping, we construct an equivalent industry-specific price index and use as deflator when necessary.

analogously construct annual weights for a firm's contribution to the total production value of a COICOP group. Thus, for each product group, our measure comprises the ULC of a set of firms selling products within that group, appropriately weighted by their respective contribution.

We perform several rounds of cleaning of the data underlying the ULC measure. To begin with, we drop a small number of firms never reporting positive sales or displaying extreme outlier values. With regards to the IPI data, we account for a time-series break stemming from a methodological change in the data collection procedure. Specifically, using three months of overlapping data around the break, we compute a quota for each firm representing how much the change affected their reported sales, which allows us to generate coherent sales numbers throughout the sample period. Note that this procedure is equivalent to the one applied in the construction of the official IPI. With regards to the UC data, a small number of firms consistently exhibit negative personnel costs. This is assumed to be due to a reporting error (i.e. costs are reported as negative values), thus, we use the absolute value of this variable.

3 Empirical Specification

To evaluate the price pass-through from producer to consumer prices, we estimate local projections (Jordà, 2005). Specifically, our baseline specification consists of a set $h \in \{0, \ldots, H\}$ of regressions defined by,

$$\begin{aligned} ln(CPI_{j,t+h}) - ln(CPI_{j,t-1}) = \alpha_j^h + \alpha_m^h + \beta^h(ln(PPI_{j,t+h}) - ln(PPI_{j,t-1})) \\ + \sum_{l=1}^{6} \lambda_1^{l,h} ln(PPI_{j,t-l}) + \sum_{l=0}^{6} \lambda_2^{l,h} ln(CPI_{t-l}) + \epsilon_{j,h,t}, \end{aligned} \tag{1}$$

where subscript j denotes COICOP product group and α_m are month dummies to account for seasonal variation in price-setting. The local projections described in equation (1) will be estimated using $ln(PPI_{j,t})$ as an instrument in the baseline set-up. Thus, the β^h coefficients in equation (1) will capture the cumulative pass-through elasticity of producer prices changes today onto consumer prices up to horizon h, conditional on the controls included in the specification. Although we do not identify the impulse response of consumer prices to a structural producer price shock, we specify a model that mimics this approach as closely as possible in a reduced-form setting. First, by including lags of $ln(PPI_{j,t})$ we aim to eliminate dynamics due to past structural shocks on the producer side, and thus only relying on variation in producer prices that is driven by (a linear combination of) contemporaneous structural shocks on the producer side. Secondly, to condition out shocks common to both consumer- and producer pricing, we include the current value as well as lags of the log of the overall aggregate CPI index to the specification.[5] Finally, the error term $\epsilon_{j,h,t}$ will be a linear combination of structural shocks (from t to $t+h$) specific to the consumer side of pricing. This error term is non-standard and in the Appendix we experiment with clustering on the 2-digit COICOP level and show that even this very conservative approach of computing error-bands does not change the baseline finding.

One concern may be that the structural shocks specific to the consumer side of pricing may actually affect producer-side pricing through a more complicated interplay in pricing than outlined in textbook versions of pricing models. To handle this, we also derive results from using an alternative IV approach. Here we use our measure of ULC for the producing firms (discussed above), which is a measure of marginal cost in a large class of macroeconomic models, as an instrument for the cumulated change in producer prices. The rationale is that, conditional on common shocks to consumer- and producer price-setting, the instrument isolates variation due to structural shocks driving marginal production cost and ensures the direction of causation in the regression outlined in equation (1).[6]

Finally, to keep things comparable, we estimate all models up to $h = 24$, and then plot the impulse responses as long as they are informative. This means that we drop the last 24 months in our data in order to have identical sample periods in the estimation of all horizons. When studying potential changes in the pricing behavior during the recent COVID- and high-inflation

[5] Including time fixed-effects instead of the current value as well as lags of the log of the overall aggregate CPI index does not change the baseline results qualitatively.

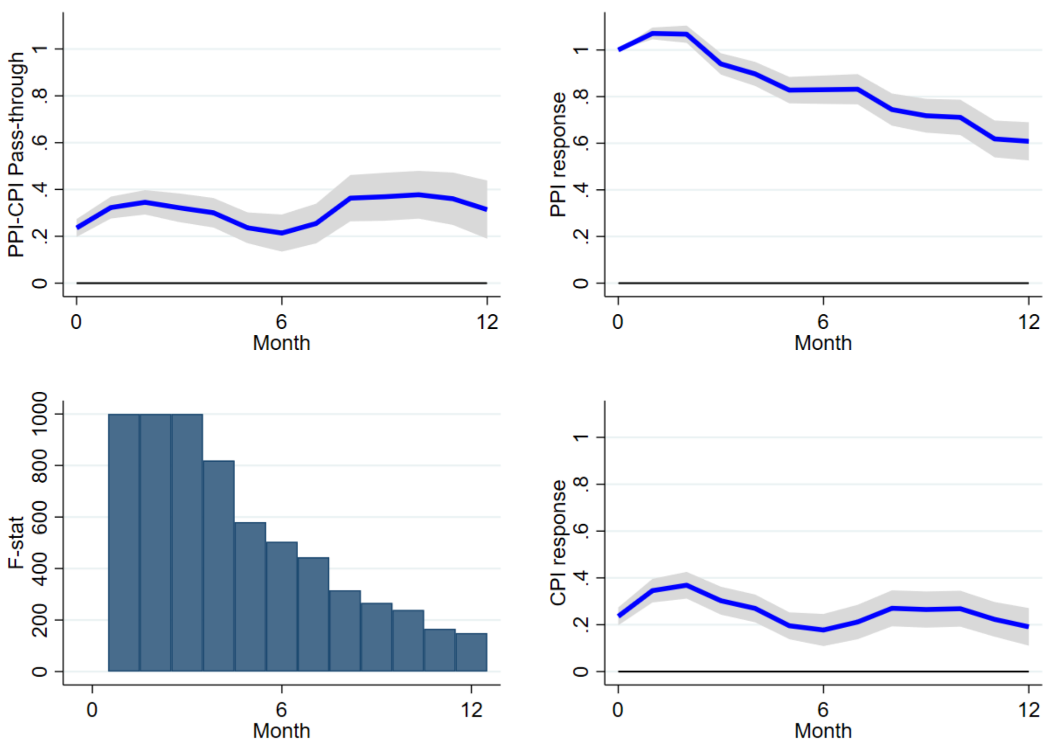
[6] Importantly, Carlsson and Skans (2012) show empirically that firm-level unit labor (or marginal cost) is independent of the scale of operation of the firm.

period, however, this procedure is untenable. Thus, in this particular exercise we set $H = 4$.

4 Results

Figure 1 shows our baseline results relying on equation (1). In the top right panel of Figure 1, we plot the results from the dynamic first-stage regressions together with 90-percent confidence bands. We see that a one percent (idiosyncratic) increase in current (COICOP group) producer prices leads to a dynamic response in producer prices that is halved in 12 months (and reverts back to zero within 24 months). In the bottom right panel, we plot the reduced-form regression, replacing the cumulated producer-price change with the log of the current producer price on the right-hand side of equation (1). The plotted impulse response for the reduced-form specification is similar in shape to the first-stage impulse response, indicating that consumer pricing patterns add little dynamics to how marginal-cost changes on the production side pass through to consumer prices. This finding is also illustrated in the top-left panel displaying the IV-response, which technically is given by the ratio of the bottom to the top two impulse responses to the right. As we see from the figure, the price pass-through is very rapid. Within the same month the pass-through elasticity is about 0.25, rising to 0.35 over the two coming months and then stays approximately at this level. Interestingly, the results for the 12-month horizon are comparable to the annual pass-through estimates between 0.27 and 0.33 of marginal (unit labor) cost from Carlsson and Skans (2012), obtained using annual firm-level price data for Sweden. In the supply chain, the marginal cost of a product sold on the consumer market can be measured by the producer price of that good, see e.g. Eichenbaum et al. (2011) for a discussion and application. Viewed as this, we see a very similar long-run pass-through of marginal cost (producer prices) onto consumer prices even when we aggregate firms to COICOP groups. Also, the very fast pass-through does point away from Calvo-style staggered contracts being important in the consumer sector. Instead, the evidence points towards a flexible- or menu-cost model where a large and self-selected share of price changers rapidly perform the bulk of the overall group-level adjustment,

Figure 1: Baseline Results



Notes: Top Left Panel: Cumulative Impulse Response of Producer Prices on Consumer Prices estimated with baseline model. Top Right Panel: First-stage results. Bottom Left Panel: F-Statistics from first stage by horizon h. Bottom Right Panel: Reduced-form results.

which continues over time and upholds a more or less constant group-level pass-through.[7]

Due to the very granular-level data we use for our analysis, the estimates are relatively precise with tight confidence bands.[8] In general, we see that the first-stage F-statistics, displayed in the bottom left panel of Figure 1, are substantial at short horizons,[9] but drops off at around 12 months where the uncertainty of the IV estimates starts to increase and where we choose to cut

[7]Note though, that in the limit when the price-change probability of a firm goes to unity, the Calvo model becomes a flexible pricing model.

[8]In the Appendix we present results from clustering the standard errors on the 2-digit COICOP level. Although, this yields too few clusters for conventional analysis and is subject to qualifications, using a students-t approach as recommended by Cameron and Miller (2015) in this situation does not change the results qualitatively.

[9]To make the bottom left panel of Figure 1 informative, we do not display F-statistic values exceeding 1000.

the graphs.

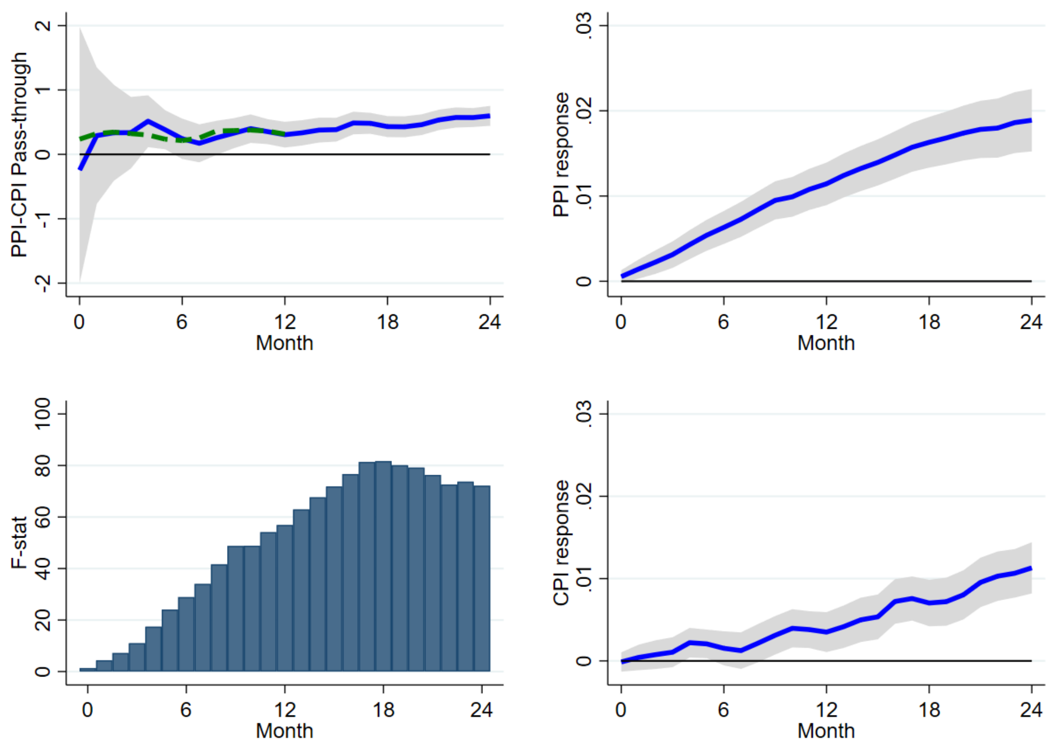
Next, we present IV-results from using the log of current values of our weighted ULC measure as instrument for the cumulated change in producer prices. In the top right panel of Figure 2, we plot the results from the dynamic first-stage regressions. As we can see from the plot, the cumulated pass-through from the current ULC to current and future producer prices is gradually increasing over the 24 months going forward (where additional analysis indicates that the producer price response peaks and then start to revert back to zero). Moreover, studying the dynamics of the ULC measure shows a similar pattern as compared to the first-stage results in the previous analysis, where the response dies of after 24 months (see Figure A1 in the Appendix). This prolonged pass-through from marginal cost to prices in the production sector allows us to estimate impulse responses with precision much further out than in the previous analysis. Moreover, this finding is in line with nominal pricing rigidities in producer prices. Specifically, this pattern is consistent with a Calvo model of pricing in the production sector, where a (small) share of firms within the group are allowed to change prices every month, generating a sluggish group-level price response to a marginal-cost change and where prices stay up even when the cost has reverted back to zero due to nominal contracts. This Calvo-style pattern is also consistent with the lack of any selection effects in Swedish micro-level producer price setting reported in Carlsson (2017). Another indication of a slow cumulative response of producer prices to a marginal cost change is the evolution of the F-statistics from the first-stage across horizons as shown in the bottom left panel of Figure 2. The F-statistic gradually increases over time up to about 18 months, reaching levels around 10 after three months. This indicates that the initial part of the estimated impulse responses will be associated with higher uncertainty due to the low relevance of the instrument for the very short horizon. In the bottom right panel we plot the reduced-form regression, replacing the cumulated producer-price change with the log of current ULC on the right-hand side of equation (1). The plotted impulse response for the reduced-form specification is similar to the first-stage impulse response, once more indicating that consumer pricing patterns add little dynamics to how marginal-cost changes on the production side pass through to consumer prices. This is also consistent with the fast and constant adjustment displayed in the top-left panel showing the IV-response. This figure also plots the baseline response from the top left panel of Figure 1 in a dotted green pattern. As can be seen from the graph, the baseline and the ULC IV responses are very similar except for the very initial response (estimated with a weak instrument in the ULC IV case), indicating that that there are no important feedback effects from consumer pricing to producer pricing in the supply chain.[10] In general, we see that the low F-statistics at short horizons are reflected in substantial uncertainty in the IV estimates, whereas the uncertainty is markedly reduced for horizons four months out or longer.

To explore heterogeneity across product groups, we next split the COICOP codes into two groups by the frequency of which consumer prices change measured from the CPI microdata and apply our baseline specification on each sub-sample.[11] In particular, we compute the price-change frequency as the average number of price changes in a year for each COICOP code, applying annual product-specific weights when aggregating from product- to COICOP-level and then taking the unweighted mean across the sample period. The exact partition into groups with high and low price-change frequency is presented in Table A2 in the Appendix. In the high-frequency group, which constitutes 27 percent of the weight in the total CPI basket, the mean [median] price-change frequency for a product is 6.8 [7.1] times a year. In the low-frequency group, the corresponding numbers are 21 percent and 2.1 [2.1]. Thus, while the average product in the high price-change frequency group changes prices around every second month, the average product in the low price-change frequency group changes prices every sixth months suggesting significant differences in the degree of price stickiness across our micro price data. Particular COICOP groups that are classified as low-frequency groups are for example motor cars, furniture and carpets, and bicycles. Groups showing a high price-changing frequency are for example fuels for

[10]Note that the level of effects in the first stage and reduced form regressions are an order of magnitude lower that what we expect from previous studies. Thus, the scaling of the IV results is very important for interpreting the level of the pass-through and the weighted ULC measure we use should only be thought of as an instrument capturing movements in marginal cost and not a measure of marginal cost per see.

[11]We also experimented with sample splitting the corresponding PPI groups by price-change frequency and estimating the first stage of the ULC IV specification separately on each sub-sample. This does not yield any additional insights however and the estimated first-stage responses just display a somewhat higher/lower slope as compared to the the pooled response displayed in the top right panel of Figure 2.

Figure 2: ULC IV Results

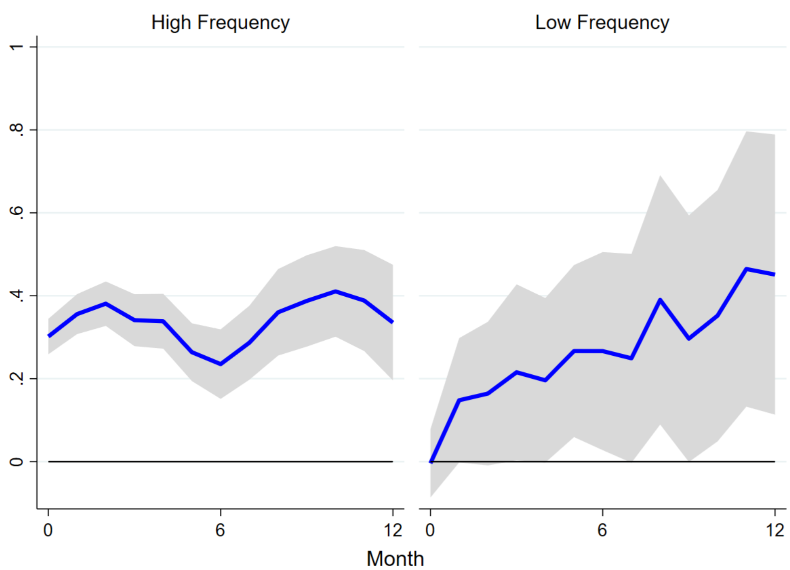


Notes: Top Left Panel: Cumulative Impulse Response of Producer Prices on Consumer Prices using current ULC as instrument in blue solid (baseline results depicted in green dashed). Top Right Panel: First-stage results. Bottom Left Panel: F-Statistics from first stage by horizon h. Bottom Right Panel: Reduced-form results.

transportation, fruits, and meat.

In Figure 3, we present the results from estimating our baseline model for the high and low price-change frequency groups separately. Comparing the impulse response functions across groups, we see very different patterns. In the high-frequency group, we see a very fast and constant response of consumer prices to producer prices (or marginal cost) where the full adjustment is complete within two months, indicating a flexible- or a menu-cost style pricing behavior. In the low-frequency group, we instead see a prolonged gradual adjustment continuing well into the 12-month horizon in line with a Calvo-style pricing behavior. Overall, this heterogeneity in impulse response indicates that the price-setting behavior is substantially different across these groups. Thus, looking at the overall response masks important insights about heterogeneity in consumer price-setting behavior. Moreover, when using disaggregated PPI data to predict the future development of CPI inflation, it strongly matters which COICOP group we are looking at.

Figure 3: Results by Price-Change Frequency Groups

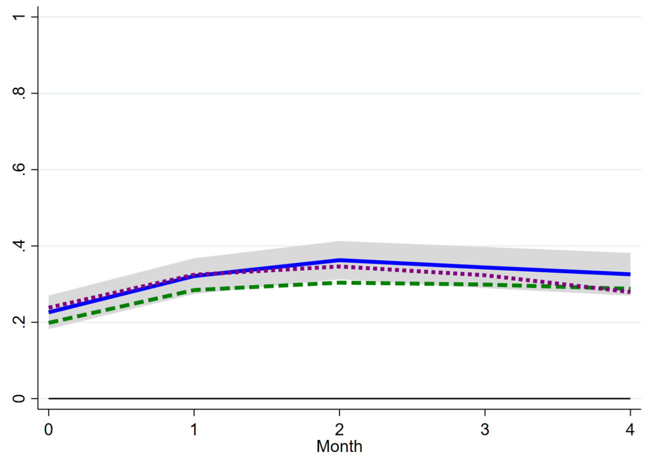


Notes: Cumulative Impulse Response of Producer Prices on Consumer Prices estimated with baseline model on sample splitted at the COICOP level by price-change frequency in consumer prices.

Next we turn to several robustness exercises. In Figure 4, we depict the results from redoing the baseline estimation, but dropping either the COVID period (from January 2020 and onwards) or the high-inflation period (from April 2021 and onwards). As is apparent in the figure, the estimated price pass-through shows only marginal differences compared to our baseline estimates. Note here that in these two exercises we change the maximum horizon in the estimation to four months in order to save on the data in the relevant periods, which are both positioned at the end of the sample.

We also tried to do the analysis in terms of regular prices contained in the CPI data, thus removing

Figure 4: Results from Dropping the COVID- or the High-Inflation Period



Notes: Cumulative Impulse Response of Producer Prices on Consumer Prices estimated with baseline model adjusted to $\max(h) = 4$. Blue line and error bands denote results from the full sample. Green dashed line denotes results from dropping the Covid period (from January 2020 and onwards). Purple dotted line denotes results dropping the high inflation period (from April 2021 and onwards).

temporary sales from the analysis. This yields qualitatively similar results in terms of the fast dynamics and the long-run response, although slightly smaller quantitatively, see Figure A3 in the Appendix. Apparently sales are not used in a systematic way to affect price adjustment, in line with the argument of Kehoe and Midrigan (2015) that sales cannot be used to handle persistent shocks due to their temporary nature.

5 Conclusion

This paper estimates the price pass-through from producer to consumer prices, using product-level data from the official Swedish producer- and consumer price index. We document robust evidence of a significant price pass-through and verify that the direction of causation in our results goes from producer prices to consumer prices. Our findings are in line with theoretical models emphasizing production inter-linkages across sectors. The granular analysis provided in the paper shows that a pooled analysis hide important heterogeneity across individual product groups. CPI groups with a higher price-change frequency display an almost immediate and constant adjustment, whereas the lower-frequency group display a prolonged gradual adjustment. Finally, the data allows us to study the recent COVID- and high-inflation periods, but we do not find any evidence that the pass-through is significantly different in these episodes.

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APPENDIX

A1 PPI-CPI merge

Table A1 displays the CPA codes from the PPI data that are included in the analysis. More specifically, these are the CPA codes that can be linked to a COICOP code that exists in our CPI data, using correspondence tables available at Eurostat. Once this link is established, PPI prices within these CPA groups are aggregated to the COICOP level using product-specific weights, which is the level at which the analysis is carried out. Out of 222 CPA codes that exists in the PPI data in total, we are able to link 144 to a COICOP code in the CPI data.

Table A1: Merged CPA codes

08.92	10.82	14.13	20.14	23.13	26.30	28.15	31.00
10.11	10.83	14.14	20.15	23.19	26.40	28.22	31.01
10.12	10.84	14.19	20.20	23.41	26.51	28.23	31.02
10.13	10.85	14.31	20.30	23.69	26.60	28.24	31.03
10.20	10.86	14.39	20.41	23.70	26.70	28.25	31.09
10.31	10.89	15.11	20.42	24.42	26.80	28.29	32.12
10.32	10.92	15.12	20.51	25.40	27.11	28.30	32.13
10.39	11.06	15.20	20.52	25.71	27.12	28.49	32.20
10.41	11.07	16.24	20.53	25.72	27.20	28.94	32.30
10.42	12.00	16.29	20.59	25.73	27.32	29.10	32.40
10.51	13.20	17.12	21.20	25.91	27.33	29.20	32.50
10.52	13.91	17.21	22.11	25.92	27.40	29.31	32.91
10.61	13.92	17.22	22.19	25.93	27.51	29.32	32.99
10.62	13.93	17.23	22.21	25.94	27.52	30.12	33.12
10.71	13.94	17.29	22.22	25.99	27.90	30.30	33.13
10.72	13.95	18.12	22.23	26.11	28.11	30.91	33.15
10.73	13.96	19.20	22.29	26.12	28.13	30.92	33.17
10.81	13.99	20.13	23.12	26.20	28.14	30.99	33.19

Notes: CPA codes from the PPI data that we can map to COICOP codes in the CPI data and thus are included in the baseline analysis.

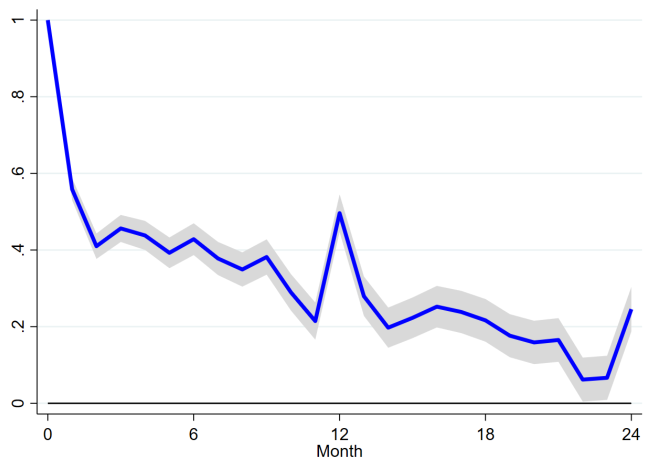
A2 ULC Dynamics

This section reports results on the dynamics of our ULC measure. Specifically, we estimate the following model with OLS:

$$\begin{aligned} ln(ULC_{j,t+h}) - ln(ULC_{j,t-1}) = \alpha_j^h + \alpha_m^h + \beta^h(ln(ULC_{j,t})) \\ + \sum_{l=1}^{6} \lambda_1^{l,h} ln(ULC_{j,t-l}) + \sum_{l=0}^{6} \lambda_2^{l,h} ln(CPI_{t-l}) + \epsilon_{j,h,t}, \end{aligned} \tag{A.1}$$

and plot the results for β^h in Figure A1.

Figure A1: ULC Dynamics



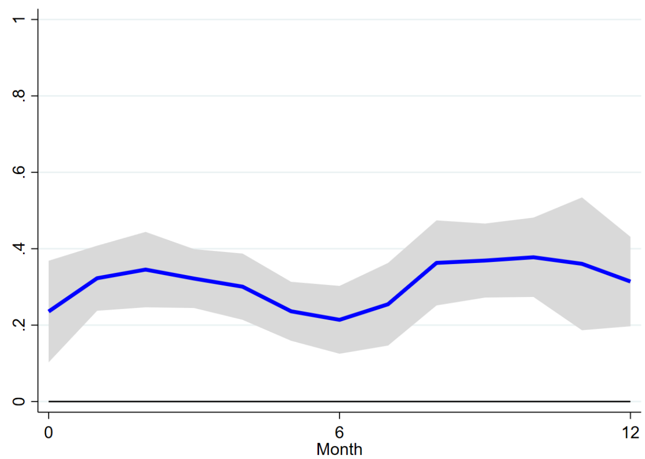
Notes: Estimated using the model outlined in equation (A.1).

The jagged pattern in Figure A1 is due to the fact that we mix annual (wage sum) and monthly information (production) in the ULC measure.

A3 Clustering

In this section we present results from clustering the standard errors on the 2-digit COICOP level. This yields only nine clusters, which is too low for conventional analysis. What we do here is to follow the recommendation of Cameron and Miller (2015) and use a students-t distribution with eight degrees of freedom. The result of this is depicted in Figure A2. Although a very conservative approach to inference, it is reassuring that the clustering does not change any conclusions from the baseline exercise qualitatively.

Figure A2: Baseline Regression with Clustered Standard Errors



Notes: Cumulative Impulse Response of Producer Prices on Consumer Prices estimated with OLS using error bands clustered on 2-digit COICOP codes.

A4 Price-change frequency

Table A2 presents the average frequency of price change in a year by COICOP codes included in our sample and the partitioning of the COICOP groups into a high- and a low-frequency group.

A5 Sales-adjusted prices

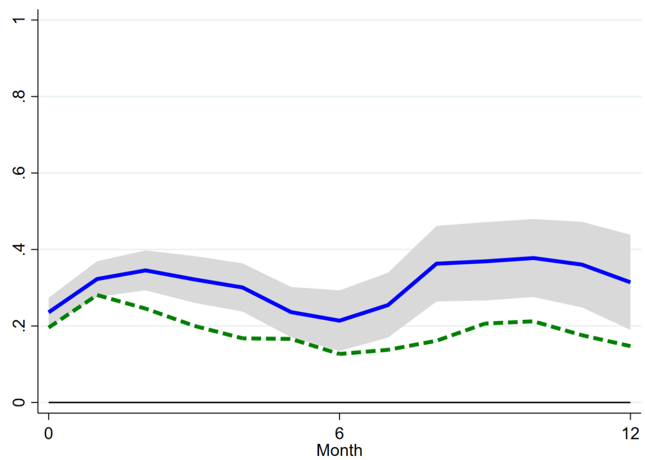
Figure A3 presents results from estimating equation (1) using sales-adjusted (i.e. regular) prices from the CPI microdata. It is noted that the pass-through dynamics remains similar when removing the effects of sales, although it becomes slightly lower throughout the estimation horizon.

Table A2: COICOP codes by price-change frequency

COICOP code	**Label**	**Frequency**
	Low-frequency group	
07.1.2	Motor cycles	0.942
9.2	Durables for recreation	1.124
07.2.1	Spare parts for transportation	1.224
07.1.1	Motor cars	1.358
5.4	Household utensils	1.406
5.1	Furniture and carpets	1.512
07.1.3	Bicycles	1.858
12.3	Personal effects	1.923
3.2	Footwear	2.111
2.2	Tobacco	2.117
12.7	Fees and services n.e.c.	2.362
5.2	Household textiles	2.428
3.1	Clothing	2.757
8.2	Telephone equipment	3.035
9.5	Newspapers and books	3.085
5.3	Household appliances	3.427
6.1	Medical products	3.628
	High-frequency group	
5.5	Tools for house and garden	3.904
9.3	Recreational items	4.131
9.1	Audio-visual and photo equipment	4.882
12.1	Personal care	5.618
5.6	Routine household maintenance	6.285
01.1.9	Food n.e.c.	6.342
01.1.8	Sugar, jam and confectionery	6.509
01.1.3	Fish and seafood	7.022
01.1.1	Bread and cereals	7.106
01.1.2	Meat	7.157
01.2.2	Mineral waters and soft drinks	7.296
01.1.4	Milk, cheese and eggs	7.413
01.1.5	Oils and fats	7.604
01.1.7	Vegetables	7.779
01.2.1	Coffee, tea and cocoa	7.911
01.1.6	Fruit	7.929
07.2.2	Fuels for transportation	10.55

Notes: Average number of price changes in a year by COICOP codes included in the sample. The frequency number is calculated as the weighted average frequency of all products within each COICOP code (using product-specific weights), and then as the unweighted average across all months in our sample.

Figure A3: Results with sales-adjusted prices



Notes: Cumulative Impulse Response of Producer Prices on Consumer Prices estimated with OLS. Blue line and error bands denote the baseline results. Green dashed line denotes results when using sales-adjusted prices from the CPI data.

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