

# The extensive and intensive margin of price adjustment to cost shocks: Evidence from Danish multiproduct firms <sup>\*</sup>

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## Abstract

This paper studies price adjustment in a novel monthly dataset of individual product prices of multiproduct firms, merged with firm-level balance sheet and cost data. The theoretical literature on price setting has pointed out that the interdependence between the decision to whether or not change prices (the extensive margin) and the actual amount by which prices change (the intensive margin) contributes to determine the real effects of monetary policy. We estimate the adjustment to shocks to firm-level import costs and energy costs (due to oil supply shocks) along extensive and intensive margins, modelling them jointly to address endogenous selection bias due to state-dependent pricing. In the first step, we estimate the probability of price changes over horizons from 1 to 24 months (extensive margin) using a multinomial logit model. There is evidence of synchronization of adjustment decisions within firms, especially as the number of goods increases, in line with price-setting models of multiproduct firms. We find evidence of state dependence as the probability of price adjustment over time is affected by cost shocks, but also by aggregate variables such as inflation and exchange rates. Using first-step estimates to correct for selection bias, similarly to Heckmans classic approach, we find that state-dependence translates only into a small bias in the intensive margin conditional on price adjustment. Moreover, pass-through of energy and import cost shocks is quite heterogeneous across sectors and firms. Gradual adjustment to energy costs mainly reflects faster price responses in intermediate and energy intensive sectors, in line with pipeline pressures along the supply chain. For import-cost shocks, pass-through of larger firms with more products is lower than that of smaller firms with fewer products. Since the latter shocks have a much smaller effect on competitors' prices than shocks to energy costs, our findings are consistent with the presence of strategic complementarities in price setting.

*JEL classification:* D22, E31, F41

*Keywords:* producer prices, cost shocks, nominal rigidities, strategic complementarities

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# 1 Introduction

Price adjustment by firms is lumpy: individual good prices alternate between long spells in which they are unchanged, and large but also small increases and decreases, largely idiosyncratic, in "reset" prices. State-of-the-art macro models of price setting by firms stress the relevance of lumpiness and heterogeneity in shaping aggregate inflation determination. Specifically, the theoretical literature on price setting has pointed out that the interdependence between the decision to whether or not change prices (the extensive margin) and the actual amount by which prices change (the intensive margin) contributes to determine the real effects of monetary policy. Menu costs models of multiproduct firms have been shown to be able to generate empirically plausible real effects of monetary policy because of within-firm price synchronization (Alvarez and Lippi, 2014) or many small cost shocks (Midrigan, 2011); this is particularly so when they also feature some degree of time-dependence in price changes (Alvarez et al. (2016)). These mechanisms attenuate "selection bias" due to the interaction between the extensive and the intensive margin of price adjustment under menu costs, namely that the prices which are more likely to change are those farther from their desired level, so that reset prices display large(r) changes. Microeconomic evidence on actual price decisions of multiproduct firms is thus crucial to understand the monetary transmission and aggregate inflation determination.

This paper studies price adjustment in a novel monthly dataset of prices of multiproduct firms, merged with firm-level balance sheet and cost data, including monthly wages and intermediates. Specifically, we use monthly producer price micro-data from the dataset that is used to compute the producer price index (PPI) by the Danish statistical office.<sup>1</sup> A crucial feature of the data that makes it relevant to an analysis of pricing by multiproduct firms is that there is substantial variation in the number of goods across more than 1,000 firms. This allows us to study how price setting features vary with the number of goods. Moreover, PPI micro data are especially useful to analyze in light of the above literature, as noted already by Bhattarai and Schoenle (2014), since they are consistent with the basic assumptions of virtually all price-setting models in macroeconomics, where it is producing firms that set prices (rather than retailers whose prices are comprised in the CPI). A similar analysis of producer pricing decisions is not feasible with CPI data since the CPI sampling procedure maps to stores, so-called "outlets", which may sell goods from any number of firms, including imports. This makes pricing a complicated web of decisions that involves the whole distribution network. Moreover, it is generally also not possible to identify the producing firms for specific CPI items. In contrast, a further advantage of our dataset is that we can link prices to

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<sup>1</sup>See Nakamura and Steinsson (2008) for a description of US PPI data; PPI microdata of other European countries were analyzed in Vermeulen et al. (2012).

balance sheet and cost data at the firm level.<sup>2</sup>

We first document key descriptive properties of price dynamics across firms, finding that these statistics are broadly invariant to the number of goods firms produce, in contrast with the predictions in multiproduct firm models with menu costs common across goods. However, we show that the (unconditional) size distribution of price changes is quite leptokurtic and thus similar to that generated by multiproduct firm models when they also allow for some degree of time dependence along with menu costs. Remarkably, we find that also firm-level variable costs are similarly leptokurtic, with a large proportion of very small cost changes, in line with assumptions in the models of Midrigan (2011) and Karadi and Reiff (2019).

Second, we exploit the richness of our dataset to estimate the pass-through of cost shocks along extensive and extensive margins, modelling them jointly to address endogenous selection bias due to state-dependent pricing decisions. Specifically, it is possible to show that in the general class of state-dependent pricing models studied by Alvarez and Lippi (2019), selection bias conditional on changing prices in response to a permanent cost shock is lower the higher the degree of time-dependence in the decision to change prices. In order to address and estimate selection bias, we rely on econometric techniques from labor economics, adapting them to a dynamic setting to estimate with local projections the impulse responses to shocks to energy costs (due to oil supply shocks) and to firm-level import costs.

In our first step, we model the probability of price changes over horizons from 1 to 24 months (extensive margin), by using a flexible multinomial logit model, after Bourguignon et al. (2007). We find that there is evidence of synchronization of adjustment decisions within firms, especially as the number of goods increases. Namely, within a multiproduct firm the probability that a given price increases is larger the larger the fraction of other prices that are decreasing. We also find evidence of state dependence as the probability of upwards and downwards adjustment over time is affected by our cost shocks, but also by aggregate variables such as CPI inflation and even exchange rates.

Concerning the intensive margin conditional on price adjustment, we find that state-dependence does not translate into a strong selection bias. Moreover, pass-through of shocks to import and energy costs is quite heterogeneous across sectors, and firms of different size, respectively. These findings support menu cost models with imperfect price change synchronization, but also other sources of attenuation in selection such as time dependence and/or predominant small (unobserved) shocks. Namely, since our shocks to energy and import costs are well approximated by random

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<sup>2</sup>A second advantage of PPI micro data, relative to consumer prices, is that they contain very few “sales” prices (namely very short-lived price changes that are quickly reverted, see e.g. Bils and Klenow (2004) and Nakamura and Steinsson (2008)). For this reason, PPI microdata do not necessitate any necessarily ad-hoc “filtering” to make them amenable to interpretation through the lens of standard price setting models. This is especially useful in econometric analyses like ours (we confirm this feature in our dataset below).

walks, strong selection would imply that OLS estimates of price impulse responses conditional on adjustment should converge from above to their medium run values, when nominal rigidities are less important. They should also be above the impulse responses estimated by our two steps procedure that corrects for selection bias using estimates from the discrete choice first step. Instead, we find that impulse responses to both shocks do not overshoot in the short run; especially price adjustment to energy cost shocks is gradual over time, consistent with incomplete pass-through within a year Ganapati et al. (2020). This gradual adjustment mainly reflects sectoral heterogeneity of the position in the supply chain and the intensity of direct and indirect use of energy, with faster price adjustment in intermediate sectors and sectors highly intense in energy both directly and indirectly. These results provide novel micro-based evidence on the debate about the propagation of idiosyncratic and more common shocks to aggregate inflation (see e.g. Boivin et al. (2009)). Firm-specific import cost shocks elicit a faster adjustment than energy cost shocks, whose effects instead gradually build up through different sectors along the supply chain, in line with the pipeline pressures view (see e.g. Smets et al. (2018) or Duprez and Magerman (2019)). Finally, concerning firm heterogeneity, for import cost shocks we find that pass-through of larger firms with more products is lower than that of smaller firms with fewer products. Given their idiosyncratic nature, the latter shocks have a much smaller effect on competitors' prices than energy costs, implying that our findings are consistent with the presence of strategic complementarities in price setting.

The rest of the paper is organized as follows: Section 2 describes our datasets (while details are relegated to the appendix) and presents key descriptive statistics on price changes, where we focus on the multiproduct dimension of firms. Section 3 explains the method we use to estimate structural pass-through coefficients in a way that accounts for both sticky prices and strategic complementarities. Section 4 discusses the results of our empirical analysis of two (random walk) cost shocks: a oil supply shock to energy costs, as well idiosyncratic import cost shocks at the firm level.

## 2 Data and descriptive statistics

Before turning to our investigation of price adjustment in response to structural cost shocks, we find it useful to provide a description of our dataset. The main part of the data we compile consists of the confidential microdata underlying the Danish producer price index from 1993 to 2017. In our analysis, we will leverage the fact that we can link the producer price data to high-frequency statements on sales and cost, as well as the degree of competition in the market the good is sold. By the same token, we report common descriptive statistics on unconditional price adjustment in

our dataset of multiproduct firms, following Bhattarai and Schoenle (2014). However, in contrast to the latter paper, we find that across Danish firms with different numbers of goods there are very few differences in aggregate statistics on price adjustment, such as frequency, size, direction, and dispersion of price changes. These findings are consistent with some specifications of the fixed costs of changing prices at the firm level in Alvarez and Lippi (2014) and Bonomo et al. (2019), where those costs increase with the number of price changes, rather than being constant across them.

## 2.1 Producer prices

The Danish PPI contains monthly price quotes of actual transactions for 558 products, that is, particular items define by 8-digit codes according to the Harmonized Commodity Description and Coding Systems (HS). At the firm-good level, we track 5'354 goods for both domestic sales and exports. The most important firms within selected areas are requested to report prices in order to ensure that the producer price index covers at least 70% of Danish production. Appendix crefsec:dataapp describes the multi-stage sampling design.

This is the first paper that uses this dataset for the analysis of price rigidity. Therefore, and to benchmark moments of the data against the U.S. PPI more commonly used in the literature, we first document key characteristics of the panel.<sup>3</sup> Note that we do not observe quantities, so we use equal weights of goods within firms and categories wherever needed.

### 2.1.1 Multiproduct firms

The PPI data allow us to identify firms according to the number of goods they produce. Using the firm identifier, we are able to determine the number of goods reported by a firm in a given month, and to the extent that this is representative for the total number of goods produced, put special emphasis on multiproduct firms in the analysis. Following Bhattarai and Schoenle (2014), we then allocate the firms to five groups according to the mean of products reported over the sample period.

Table 1 presents descriptive statistics on the distribution of firms and products across these groups. The cutoffs used on the mean number of products reported are 1, 3, 5, and 7. The product dispersion is comparable to that in the US PPI dataset, with the exception that the dispersion of firms with the most product is higher in our data. Observe that the Danish data contains 1,140 firms, compared to more than 28,000 in the US PPI.

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<sup>3</sup>Two key differences relative to the US PPI data used in the literature are that first, Danish PPI prices are collected at the firm/enterprise level rather than the establishment level (“price-forming units” usually defined to be “production entities in a single location”, by the BLS); and second, that both domestic and export prices are reported. Both features of the data imply that relying on the US PPI micro data may actually lead to underestimating the number of products at the firm level.

The table also shows that while the majority of firms, around 80%, fall in bins 1 to 3, firms in bins 4 and 5 produce more goods, so that they account for a much larger share of prices than of firms. Firms in bins 4 and 5 set around 50% of all prices in our data, again comparable with U.S. data. The distribution across bins is robust to only including goods sold in the domestic market. When grouping the firms according to the number of domestic goods they sell, goods of firms with up to 3 products represent a larger share of our sample, but prices set by firms with 5 or more products still make up 40% of the dataset.

Finally, regarding firm size, the table reports two statistics, mean and median employment at the firm level, where mean employment is defined both at the firm level and as employment per average number of goods per firm. Clearly, in line with the results in Bhattarai and Schoenle (2014), firms producing more goods do not have more employees per good, but they are overall larger than firms producing less goods.

### 2.1.2 Frequency of price adjustment

Our price observations are actual transaction prices. We can therefore decompose price changes into an extensive margin of price increases/decreases and their size and thus assess the degree of price stickiness.

We first compute frequencies as the mean fraction of price changes during the life of a good. For exported goods, we define as a price change if both the value in Danish kroner and in the currency in which the price is reported change, if the two differ. Also, we do not explicitly take into account issues of left-censoring of price-spells. For our purpose, it is most relevant that we apply our method consistently across all firms. The mean adjustment frequency across all goods for the subsamples are depicted in the third panel of table 1. The mean (median) adjustment frequency in the sample is 20.6% (8.00%), corresponding to a median implied duration of a price spell of 12 months. Price adjustments are therefore slightly less frequent than in the U.S. PPI (10.8% in Nakamura and Steinsson (2008)) but very close to euro area statistics Vermeulen et al. (2012).

We further document that neither the frequency nor the size of price changes are a function of the number of products produced. We proceed as in Bhattarai and Schoenle (2014) and aggregate goods within multiproduct firms by taking the median of good-level price change frequencies, and then report moments of the firm-level distribution in table 1.<sup>4</sup> While the levels are comparable to evidence from the U.S. PPI, there is no monotone or statistically significant relationship between the number of goods produced and price adjustment statistics. Further, we find that across all

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<sup>4</sup>In the data appendix, we include replications of figures presented in Bhattarai and Schoenle (2014) in which we include 95% confidence intervals on all these statistics.

Table 1: Summary statistics by number of products

	All	1	1-3	3-5	5-7	7+
No. of firms	942	92	449	200	118	83
Mean employment (FTE)	630.5	76.4	168.4	259.2	249.3	1601.8
Median employment (FTE)	161.5	44.1	62.4	134.9	146.8	534.9
Mean employment per good	70.5	76.4	66.6	63.5	44.2	96.6
Median employment per good	32.9	44.1	25.1	34.1	24.9	51
Mean age (years)	33.5	31.5	29.6	34.1	32.0	37.5
Median age (years)	29.0	28.0	28.0	31.0	26.0	32.0
Share of total prices	100.0	1.3	20.5	22.2	18.5	37.5
Mean no. of products	9.0	1.0	2.7	4.1	5.8	19.4
Std. err. no. of products	12.9	0.0	0.5	0.6	0.5	18.6
25th percentile	3.0	1.0	2.5	3.6	5.4	8.8
Median	5.1	1.0	3.0	4.1	5.8	11.6
75th percentile	8.7	1.0	3.0	4.6	6.0	16.9
Mean adj. frequency across goods	20.6	22.6	18.4	20.3	16.4	24.2
Median adj. frequency across goods	8.0	8.1	6.1	8.0	7.1	10.0
Mean adj. freq., median good	17.9	22.1	17.6	18.5	14.2	18.9
Median adj. frequency, median good	7.0	8.0	6.3	7.7	6.8	8.8
Mean fraction of increases	68.0	67.7	67.6	67.5	70.8	67.6
Mean abs. size of price adj.	6.2	5.8	6.6	5.5	6.1	7.1
Increases only	6.0	5.7	6.3	5.4	5.7	6.6
Decreases only	7.4	6.0	7.2	7.8	7.3	8.2
Kurtosis	4.9	4.5	5.0	4.9	5.0	4.8

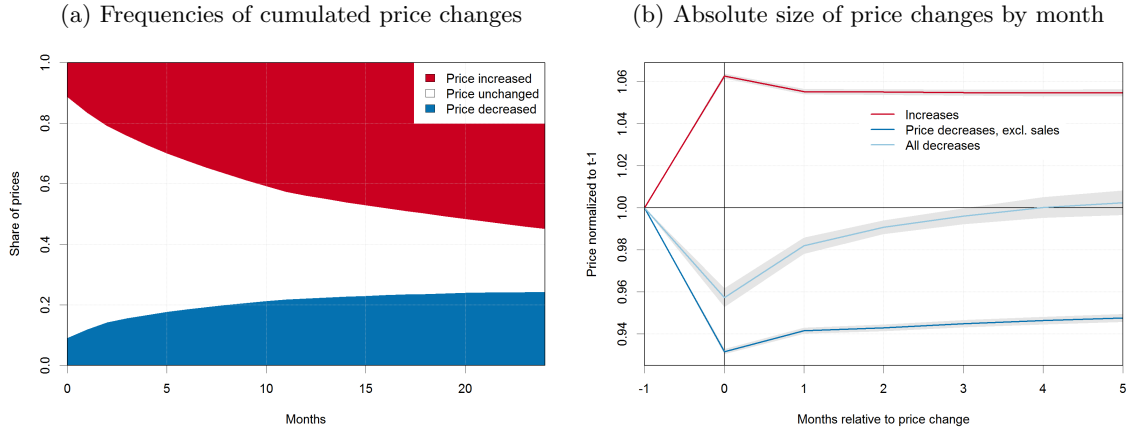
Note: Summary statistics on distribution of firms and prices across distinct bins of the average number of product reported between January 2008 and December 2017. Frequencies are reported in % per month, and computed as in Bhattarai and Schoenle (2014): Take the mean of adjustment frequencies at the good level, then compute the median frequency of price changes across goods in a firm. Finally, we report the mean and median across firms in a given subsample. Fractions are reported in percentages. We report price change statistics by broad economic categories in the data appendix.

bins more than 67% of these changes (over all non-zero price changes) are positive price changes. Firms thus adjust prices upward with similar frequency independently of the number of goods they produce.<sup>5</sup>

Since we are interested in dynamic pass-through, we also report the unconditional frequencies for cumulative price changes in figure 1a. It cumulates log price changes over a period of up to 2 years and reports, for every month, the share of prices have increased or decreased. The figure re-emphasizes the notion of price stickiness in the data: more than 30% of price spells remain unchanged after 12 months, and 20% even survive at least 24 months.

<sup>5</sup>Two notable differences could explain this: First, the Danish PPI includes export goods, but conditioning on domestically sold goods only does not change this results qualitatively. Second, the U.S. PPI data is reported at the establishment level, whereas our data is reported by the firm.

Figure 1: Price adjustments: Frequency and size of price paths



Note: (a) For every horizon  $k$ , this figure depicts the probability of having changed (increased or decreased) the price between month 0 and  $k$ . (b) Conditional on price changes in period  $t$ , this figure shows the average path of the price during the following subsequent 5 months. Sales are defined as price changes that are fully reverted after 1-3 months.

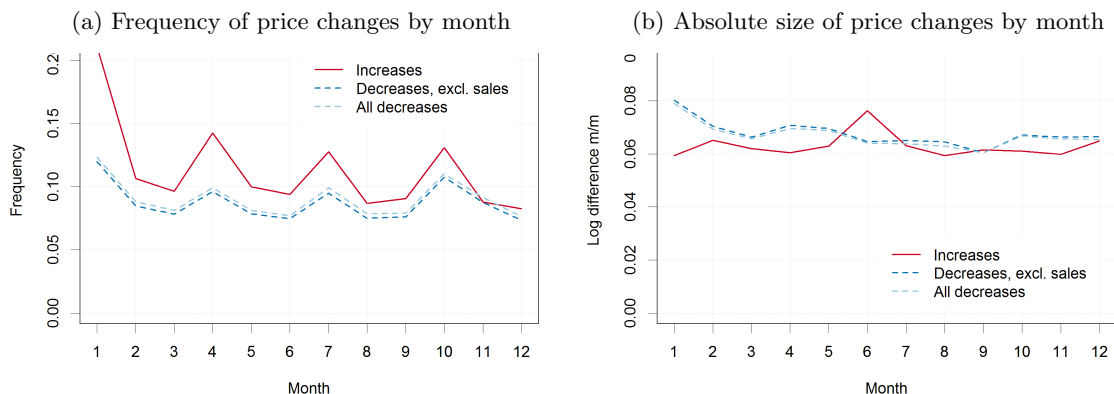
### 2.1.3 Corrections

In relation to recent studies of price adjustment using CPI micro data from scanners at retail stores, it is worth noting the following aspects of the Danish PPI data as regards temporary sales and product replacements. First, while sales are important in the CPI data as documented by Bils and Klenow (2004), Nakamura and Steinsson (2008), Berardi et al. (2015) or to a lesser degree Wulfsberg (2016), they are not a major source of price adjustments in the PPI data. In order to check the relevance of sales in our data, we apply a sales filter similar to “filter B” in Nakamura and Steinsson (2008), where we define as a “sale” every price decrease that is fully reverted after 1, 2, or 3 months. This is the case for just 0.31% of all price observations or 3.5% of all price decreases. There is instead no evidence of “reversed sales”, i.e. temporary price increases that are fully reverted according to “filter B”. Figure 1b shows the average price index after price increases, decreases without sales and the identified sales prices separately. Interestingly, not only is the typical price decrease identified as a sale price much less persistent (by construction) than the typical non-sale price decrease, but it is also smaller. Therefore, we do not exclude sales prices from our analysis (but do control for them in our econometric analysis).

Second, Nakamura and Steinsson (2008) also show that for aggregate statistics on price changes, accounting for product substitutions can make a difference, especially in the CPI. In our PPI dataset, product replacements are flagged with a counterfactual price correcting for the replacement or quality adjustment. However, they are less important since only 0.7% of all price changes (including



Figure 2: Seasonality of frequency and size of price changes



Note: Mean frequency of price changes of firms per month of the year. Price changes (particularly increases) are most frequent in January, with local peaks at the first month of any quarter. Sales remain quantitatively minor and do not have a seasonal pattern different from regular price decreases.

zero changes) and 0.8% of all non-zero price changes are due to product replacements.

#### 2.1.4 Seasonality

We find a substantial seasonal component of PPI price changes, in striking similarity to Nakamura and Steinsson (2008). Figure 2 presents the median frequency (panel (a)) and the mean absolute size (panel (b)) of both price increases and decreases by month — whereas results for decreases are very similar whether we include or exclude sales. Four results stand out. First, the frequency of price changes declines monotonically over the first three quarters, and then is roughly constant. Second, in all four quarters, the frequency of price changes is largest in the first month of the quarter and declines monotonically within the quarter with the exception of September. This gives rise to the pattern of local peaks in the frequency of price changes in January, April, July, and October. Third, price increases play a disproportionate role in generating seasonality in price changes. Producer prices are twice as likely to change and increase in January than on average in other months of the year. Fourth, seasonality is much less apparent in the mean size of price increases and decreases, and if anything follows a different pattern than in the price change frequency. Mean price increases are not larger in the months at the beginning of quarters, when the frequency is higher; price decreases are larger and more frequent in January.

Overall, these results suggest some time dependence of price changes, with possibly significant implications for the transmission of shocks. Olivei and Tenreyro (2007) show that the real effects of monetary policy in the US differ depending on the quarter of the year in which the shock hits. They argue that seasonality in the flexibility of wages can explain their empirical findings. Our result

that a disproportionate number of price increases are recorded in January could point to similar effects in Denmark and even in the euro area, as Álvarez et al. (2006) also find that prices are significantly more likely to change in January in the euro area. However, the size of price changes does not seem to be much larger in January, pointing to other mechanisms beyond large seasonal changes in firms' costs or demand.

### 2.1.5 Size and distribution of price changes

The size of price changes is defined as the absolute log difference of monthly price observations, conditional on a price change. Again, we compute this at the good level, take the median across goods in a firm, and then report the mean across firms. Table 1 (bottom panel) shows that the typical price change observed is around 6.2%. Decreases tend to be marginally larger than increases. We do not find, however, that price changes vary by the number of products sold by the firm.<sup>6</sup>

In light of theories of price adjustment, we do not confirm empirical evidence of firm-level menu cost such as Bhattarai and Schoenle (2014), needed to explain a large mass of small price changes observed in the data. This excess kurtosis is a feature that is present in the Danish PPI, as figure 3 shows. To account for the heterogeneity across goods, we standardize price changes by the 2-digit HS code level, and even exclude price changes smaller than 0.1%, to account for possible measurement error Alvarez et al. (2016). The distribution of non-zero price changes has more mass around zero than would be implied by a normal distribution. It's kurtosis is 4.73 and thus closer to a Laplace distribution (with a kurtosis of 6). Interestingly, these distributions can be well approximated by the model with both random menu costs and firms with 4 or more goods studied in Alvarez et al. (2016). Overall, we find that the distribution of price changes is very similar independently of the number of goods produced by a firm, which we again include in the data appendix.

For further comparison, we report the mean and median frequency and size of adjustment by product categories in the data appendix.

## 2.2 Firms

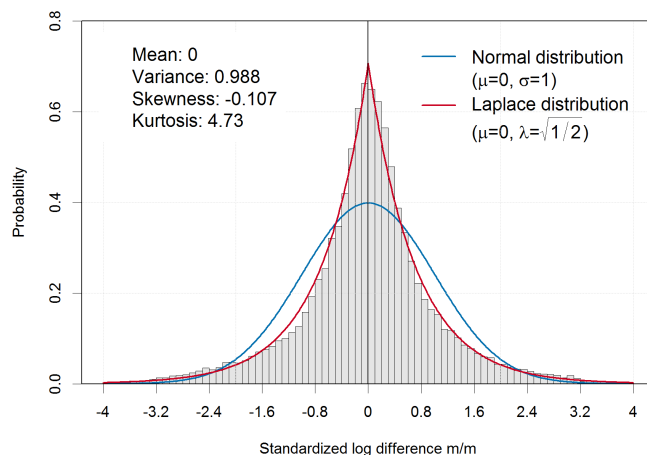
### 2.2.1 Competitors

As we will lay out below, firms' pricing decisions are a function of their competitors prices under imperfect competition. The 942 firms we include in the analysis compete on different markets. We define competitors to be firms that sell products in the same 2-digit category of the Harmonized System in the same month. 74 such product sectors are identified. The average number of competing

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<sup>6</sup>In the data appendix, we include replications of figures presented in Bhattarai and Schoenle (2014) in which we include 95% confidence intervals on the statistics of adjustment size for each bin.

Figure 3: Histograms of standardized price changes



Note: Price changes are the log difference in price, standardized by good category (first two digits of the product HS code). Price changes equal to zero or smaller than 0.1% are discarded. A normal and Laplace distribution with unit variance are superimposed.

firms in each sector is 42, whereas the first/second/third quantile of numbers of competitors for which we observe prices is 11/26.5/47. We will refer to the geometric average of all known firms in the same product sector as the price change of competitors.

Figure 4a illustrates the heterogeneity in the degree of competition across goods. We do observe competitor's prices even in the markets in which there is the least competition. On the other end, 20% of goods are sold in markets where they compete against up to 10% of all goods in the data. Furthermore, the dashed line underlines the network structure of the producer price data: Because firms operate in more than one product sector, 30% of products not only face direct competition from other firms in the same sector, but also indirectly from firms operating in the same and other markets. Our data allows us to analyze the strategic complementarities at play when cost shocks are transmitted through supply chains.

### 2.2.2 Cost data

We merge the PPI survey to firm-level data on the cost structure of production using a masked firm identifier. First, data from VAT filings contains information on nominal values of total sales and exports, as well as the purchases of foreign and total intermediate inputs. Second, we merge data from annual accounting statistics in Danish private-sector firms and information on firm age and size from business registers. The accounting statistics gives us a complete picture of all the firm's cost structure at the annual frequency. Ultimately, we have access to monthly payrolls the firm

pays to all its employees. The availability of the payroll data dictates the time span (2008-2017) used in the following econometric analysis.

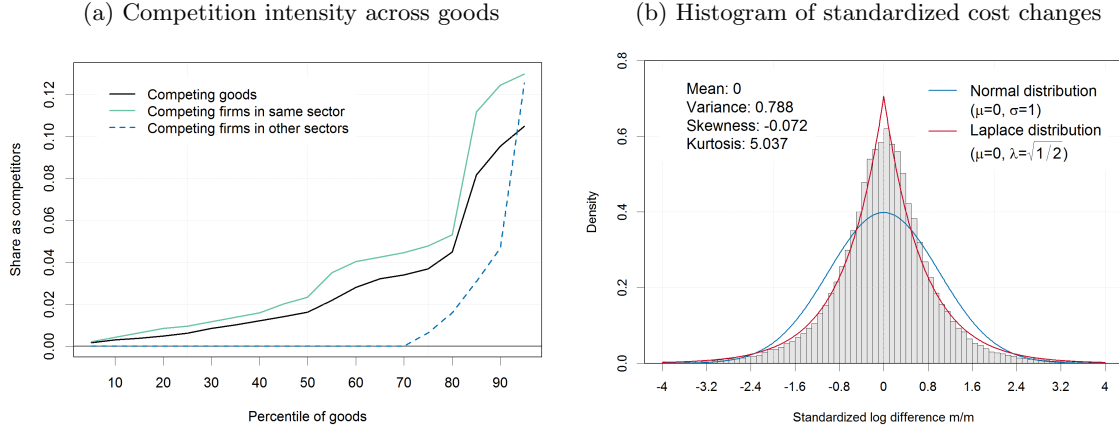
We measure variable costs as the sum of domestic and imported intermediate goods purchased according to the VAT reporting, and the monthly wage bill. Comparing the distribution of firms prices and variable costs is useful, as several theories show that the latter are crucial to account for the aggregate effects of nominal shocks. Figure 4b thus shows the standardized distribution of changes in variable cost with a superimposed normal and Lapalce distribution with unit variance. The following findings stand out. First, contrary to prices, there are very few zero cost changes in our sample. Second, the distribution of cost changes is even more leptokurtic than the price distribution, with a larger incidence of small changes. Finally, we show in the appendix the distribution of variable cost changes is less dispersed and has higher kurtosis in firms selling more products.

We focus on two different kinds of cost shocks, the first one with a predominantly idiosyncratic component, i.e. a shock to firm-specific prices of imported inputs; the second one with a predominantly common component across firms, namely oil supply shocks (which we show directly affect the price of energy in Denmark, see Appendix A.3). To obtain firm-level marginal cost, we interact the change in the respective input cost with the lagged intensity of the firm's cost structure in the respective input.

Import shares are computed using the VAT reports, by dividing the total value of imports in a given month by total cost. The changes in import prices are directly observed in the import wave of the PPI data. Since we do not observe product-level weights, we take a geometric average of import cost changes in DKK of all goods imported by the firm in a given month. If the firm does not purchase abroad, we set this to zero.

Another shock to marginal cost we will consider is energy costs due to oil supply shocks, which is more aggregate in nature. We obtain a firm-level shock by interacting the (fitted) energy price in Danish kroner with the lagged share of energy in total cost. This information is reported in the annual accounting statistics, and will measure the exposure of the firm's marginal cost to changes in import prices. The energy share includes, apart from the expenditure on refined oil and petroleum, also electricity and heating. While the share of cost spent on energy is relatively small in the median firm, its price fluctuations provide a source of aggregate shocks that are common across firms, but to which firms have different direct exposure given by their energy intensity. We provide histograms of the cost shares of imports and energy in data appendix A. To address concerns of demand-side drivers of the price of energy, we regress the energy price changes on the series of exogenous oil supply shocks provided by Baumeister and Hamilton (2019) and use the fitted values as true shocks to the cost of energy.

Figure 4: Competition and cost shock distributions



Note: (a) To illustrate the degree of competition, we define 74 product sectors according to the first two digits of the HS code. We count the number of other goods and competing firms in the same product sector for every good, and divide it by the total amount of goods and firms in the sample in the respective period. (b) Histogram of changes in variable cost measured as the sum of total intermediate purchases (domestic and import) at the monthly frequency. We exclude zero-cost changes and cost changes smaller than 0.01% and superimpose a normal and Laplace distribution with unit variance.

### 3 Estimation of dynamic price adjustment under sticky prices

In this section we briefly review some useful theoretical results on lumpy price adjustment, starting with the case when firm prices are fully flexible, and then looking at the case of time- and state-dependent price stickiness. We use these results to guide our empirical analysis.

#### 3.1 Cost pass-through under price flexibility: Intensive margin

Let  $p_{ijt}$  be the log price of one (of possible many) good  $i$  in firm  $j$ . The general price setting equation under imperfect competition for the (static) optimal (log) price  $p_{ijt}^*$  postulates that it is a function of a markup ( $\mu_{ijt}$ ) over marginal costs ( $mc_{ijt}$ ):

$$p_{ijt}^* = mc_{ijt} + \mu_{ijt}, \tag{1}$$

Under fairly general conditions, including separability of the firm-level demand for each product, (Amiti et al., forth., henceforth AIK) show that markups are a function of marginal costs and

competitors' prices  $p_{-j,t}$ , so that in first differences we obtain the following pricing relation:<sup>7</sup>

$$\Delta p_{ijt}^* = \frac{1}{1+\Gamma} \Delta mc_{ijt} + \frac{\Gamma}{1+\Gamma} \Delta p_{-j,t}. \quad (2)$$

Marginal costs are generally unobservable, but under fairly general assumptions, AIK show that they can be written as the sum of all variable input prices weighted by their respective shares in total variable costs at the firm level, plus a product-specific cost component. When assessing the pass-through of specific, observed cost shocks, they enter equation (2) by taking a shock to a specific cost component,  $\Delta c_t$ , multiply by its share of total cost,  $\phi_{jt}^c$ . Controlling for competitors' prices, this equation can be implemented in a linear regression framework.<sup>8</sup>

### 3.2 Cost pass-through under price stickiness: Extensive and intensive margin

Price pass-through of cost shocks may not be instantaneous for a variety of reasons. Regarding equation 2, this raises the following two observations. First, including unchanged prices will bias the estimates downward. This bias is present under both time-dependent and state-dependent pricing (e.g. Berger and Vavra (forth.) formally show that the bias is proportional to the frequency of adjustment). To be clear, zero price changes are crucial to understand aggregate inflation dynamics in response to cost shocks, but it is equally key to precisely estimate how much firms change their prices conditional on adjustment. This intensive margin is central to shed light on the role of real rigidities in price adjustment separately from that of nominal rigidities. Therefore, a typical solution in the empirical literature is to run pass-through regressions conditioning on non-zero price changes.

However, and this is the second observation, even conditioning on non-zero price changes in general does not allow recovering the structural pass-through coefficients, in particular under state-dependent pricing.<sup>9</sup> In this case, the above pass-through regression is biased by endogenous selection into optimally adjusting prices. Selection induces a positive correlation between the observed cost

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<sup>7</sup>When the demand for goods produced by multiproduct firms is not separable and has a different elasticity within the firm than across firms, then the good-specific markup cannot be easily expressed as simply a function of the prices of competitors of the same good. Conversely, the markup becomes a function of the sensitivity of the firm-specific demand for other goods, which in turn can be affected by competitors' prices in all these other markets.

<sup>8</sup>This approach has nevertheless the limitation that in computing  $\Delta p_{-j,t}$  we cannot easily measure prices of foreign competitors (both for domestic prices and for export prices), so that the estimated  $\frac{1}{1+\Gamma}$  may also reflect to some extent the elasticity of foreign competitors' prices to shocks to Danish imported inputs, for instance due to common suppliers in third countries.

<sup>9</sup>Optimal price adjustment under time-dependent pricing is different from flexible prices in response to the same shocks. For instance, assuming a constant markup, the optimal flexible price is given by:

$$p_{jt}^* = const + \ln C_{jt};$$

shock, and any other unobserved good-level idiosyncratic shock. To wit: in the standard menu cost model, the price of a good receiving a large idiosyncratic shock of the same sign as the cost shock of interest is more likely to be adjusted, other things equal. This selection bias is likely to be present at any horizon  $t + h$  at which the probability that the price may not change is non-negligible, making OLS estimates biased upward.

This can be formally shown using the analytical methods recently developed by Alvarez and Lippi (2019) to solve for a broad class of state-dependent models with (random walk) idiosyncratic cost shocks. These (single-good) model flexibly encompasses both the menu cost model of Golosov and Lucas (2007) and the purely time-dependent Calvo model; while in the former setting firms decide to change prices endogenously, in the latter the probability of changing prices is determined by the exogenous parameter  $\zeta$ . While we relegate the details to the appendix, Alvarez and Lippi (2019) shows that in response to a small permanent nominal cost shock  $\delta$  at  $t_0 = 0$ , in this class of models the cumulated aggregate price change (including zero and non-zero changes) at  $t_0 + t$ ,  $P(t, \delta)$ , could be approximated as follows:<sup>10</sup>

$$P(t, \delta) = \delta \left\{ 1 - \sum_{j=1}^{\infty} e^{-\zeta \left[ 1 + \frac{(2 \cdot j \pi)^2}{8\phi} \right]} \cdot t \left[ \frac{2}{1 + \frac{(2 \cdot j \pi)^2}{8\phi}} \frac{1 - \cosh(2\sqrt{\phi}) (-1)^{2 \cdot j/2}}{1 - \cosh(2\sqrt{\phi})} \right] \right\}.$$

In the expression, the parameter  $\phi \in (0, \infty)$  determines how close the model is to Golosov-Lucas ( $\phi \rightarrow 0$ ) or to Calvo ( $\phi \rightarrow \infty$ ), with intermediate values denoting an intermediate degree of time-dependence. It is possible to show that in the Golosov-Lucas model the solution is (see equation

but this coincides with the optimal reset price in the time-dependent Calvo model only when cost shocks are close to a random walk. As shown by Gagnon (2009), in a stationary equilibrium with zero inflation the optimal reset price  $P_{jt}^*$  in the Calvo model with idiosyncratic cost shocks is given by

$$\ln P_{jt}^* = \text{const} + \ln \sum_{s=0}^{\infty} (\beta \zeta)^s \exp \left[ \rho_A^s \widehat{C}_{jt} + \frac{1 - \rho_A^{2s}}{1 - \rho_A^2} \sigma_u^2 \right],$$

where  $1 - \zeta$  is the exogenous probability of adjusting prices, and idiosyncratic cost shocks  $\widehat{C}_{jt}$  are assumed log-normal as follows:

$$\begin{aligned} \widehat{C}_{jt} &= \ln(C_{jt}/\bar{C}) \\ \ln C_{jt} &= (1 - \rho_A) \ln \bar{C} + \rho_A \ln C_{jt-1} + u_t \\ u_t &\sim N(0, \sigma_u^2) \Rightarrow \widehat{C}_{jt} | \widehat{C}_{jt-1} \sim N(\rho_A \widehat{C}_{jt-1}, \sigma_u^2), \widehat{C}_{jt} \sim N\left(0, \frac{\sigma_u^2}{1 - \rho_A^2}\right). \end{aligned}$$

Therefore the reset price is the same as under flexible prices only when  $\rho_A \rightarrow 1$ , namely shocks are close to a random walk.

<sup>10</sup>The paper looks at a random-walk monetary policy shock which permanently increases marginal costs by  $\delta$ .

27 in Alvarez and Lippi (2019):

$$P(t, \delta) = \delta \left\{ 1 - \sum_{j=0}^{\infty} \frac{32}{((2+4j)\pi)^2} e^{-N \frac{((2+4j)\pi)^2}{8} \cdot t} \right\},$$

where  $N$  is the average number (frequency) of price changes per period in the Golosov-Lucas model; in the Calvo model we have instead

$$P(t, \delta) = \delta \cdot (1 - e^{-\zeta t}),$$

so that setting  $N = \zeta$  the two models have the same frequency of price changes per unit of time.

Defining with  $S(t, \delta)$  the probability of survival of an unchanged price (= fraction of unchanged prices as of  $t$  after shock  $\delta$ ), we can compute an approximation to cumulated non-zero price changes between  $t_0$  and  $t$  as the ratio  $\frac{P(t, \delta)}{1 - S(t, \delta)}$ . Clearly in the Calvo model  $S(t, \delta) = e^{-\zeta t}$ , independent of  $\delta$ , so that

$$\text{Calvo} : \frac{P(t, \delta)}{1 - S(t, \delta)} = \delta.$$

Intuitively, averaging across exogenous non-zero price changes exactly retrieves the optimal marginal price adjustment equal to the (random walk) cost shock  $\delta$ , with no selection bias. Price changes reflect both idiosyncratic shocks and  $\delta$ , but the former are just a random sample from their distribution across firms and thus wash out in the cross section.

In the Golosov-Lucas model we also have that  $S(t, \delta) = S(t)$  is independent of  $\delta$  for a small shock; non-zero cumulated price changes can be approximated as follows:

$$GL : \frac{P(t, \delta)}{1 - S(t)} = \delta \frac{1 - \sum_{j=0}^{\infty} \frac{32}{((2+4j)\pi)^2} e^{-N \frac{((2+4j)\pi)^2}{8} \cdot t}}{1 + \sum_{j=1}^{\infty} e^{-N \frac{((2j-1)\pi)^2}{8} \cdot t} \left[ \frac{2}{(2j-1)\pi} (\cos((2j-1)\pi) - 1) \sin(j \cdot \frac{\pi i \phi n}{2}) \right]} \approx \delta \frac{1 - \frac{32}{(2\pi)^2} e^{-N \frac{(2\pi)^2}{8} \cdot t}}{1 - \frac{4}{\pi} e^{-N \frac{\pi^2}{8} \cdot t}},$$

where in the last expression on the right hand side we have focused on the first (dominant) non-zero terms in the summations for simplicity. Clearly, the ratio on the right hand side is larger than 1, since

$$e^{-N \frac{\pi^2}{8} \cdot t} > \frac{2}{\pi} e^{-N \frac{(2\pi)^2}{8} \cdot t}, \forall t \geq 0;$$

this implies that averaging across non-zero state-dependent price changes overestimates the correct marginal price adjustment to the cost shock  $\delta$  because of endogenous selection into price adjustment, for all horizons  $t$ .

Finally, we can approximate non-zero price changes for the intermediate case  $\phi \in (0, \infty)$ , ob-



taining (again focusing on the dominant term):

$$\frac{P(t, \delta)}{1 - S(t)} = \delta \frac{1 - \sum_{j=1}^{\infty} e^{-\zeta \left[1 + \frac{(2 \cdot j \pi)^2}{8\phi}\right] \cdot t} \left[ \frac{2}{1 + \frac{(2 \cdot j \pi)^2}{8\phi}} \frac{1 - \cosh(2\sqrt{\phi})(-1)^{2 \cdot j/2}}{1 - \cosh(2\sqrt{\phi})} \right]}{1 + \sum_{j=1}^{\infty} e^{-\zeta \left[1 + \frac{((2j-1)\pi)^2}{8\phi}\right] \cdot t} \left[ \frac{2}{(2j-1)\pi} (\cos((2j-1)\pi) - 1) \sin\left(j \frac{\pi}{2}\right) \right]} \approx \delta \frac{1 - \frac{2}{1 + \frac{(2\pi)^2}{8\phi}} \frac{1 + \cosh(2\sqrt{\phi})}{1 - \cosh(2\sqrt{\phi})} e^{-\zeta \left[1 + \frac{\pi^2}{2\phi}\right] \cdot t}}{1 - \frac{4}{\pi} e^{-\zeta \left[1 + \frac{\pi^2}{8\phi}\right] \cdot t}}.$$

Again it is relatively straightforward to show that for  $\phi \in (0, \infty)$  the ratio on the right hand side is larger than 1 but decreasing in  $\phi$ , the degree of state dependence. This implies that the selection bias falls with the degree of state dependence.<sup>11</sup>

The conclusion is that it is important to take the extensive margin, the likelihood of price changes, into account when estimating cost pass-through at different time horizons, particularly in the short-run. Moreover, accounting for selection bias can provide direct evidence on the significance of state-dependence in shaping price adjustment.

### 3.3 Selection-bias corrected estimation

To estimate cost pass-through taking into account the non-linear extensive margin of price adjustment inducing selection, we propose the following two-step procedure, drawing from the selection bias correction approach by Bourguignon et al. (2007).<sup>12</sup> Specifically, in the first step we model selection into price adjustment as a multinomial logit, while in the linear projections in the second step we include a "bias correction" based on the first step.

Consider the following local projection model of joint extensive and intensive margin of price setting over horizons  $h = 0, \dots, H$ :

$$\begin{aligned} r_{ij,m,t+h}^* &= \gamma_m^h Z_{ij,t} + \eta_{ij,m,t+h}, & m &= -1, 0, 1 \\ p_{ij,t+h} - p_{ij,t-1+h} &= \beta^h X_{ijt} + u_{ijt+h}, & m &\neq 0 \end{aligned} \quad (3)$$

where  $r^*$  is the (profit) outcome of a categorical variable  $m$  taking the value 1 if the price increases between periods  $t$  and  $t + h$ , i.e.  $p_{ij,t+h} - p_{ij,t-1+h} > 0$ , -1 if the price decreases, and 0 otherwise,

<sup>11</sup>Formally:

$$\frac{1}{\pi} e^{-\zeta \left[1 + \frac{\pi^2}{8\phi}\right] \cdot t} > \frac{4\phi}{2\phi + \pi^2} \frac{1 + \cosh(2\sqrt{\phi})}{1 - \cosh(2\sqrt{\phi})} e^{-\zeta \left[1 + \frac{\pi^2}{2\phi}\right] \cdot t}, \forall t \geq 0.$$

Observe that for  $\phi \rightarrow \infty$  the expressions do not exactly converge to those for the Calvo model, as explained in Alvarez and Lippi (2019). Moreover, the results here on selection bias obviously are tightly related to the discussion in Section 5 in the paper on the selection effect.

<sup>12</sup>The logic is similar to a Heckman (1979) bias-correction with more than two categorical outcomes in the first step. The literature has often relied on Tobit Type II to accommodate discreteness in price changes, but given the binomial restriction of its outcome variable, the model needs to be estimated twice Berardi et al. (2015) to account for asymmetries in the probability of price increases and decreases. We argue that our multinomial approach is better suited for this purpose, as the selection will be a bi-product of estimating only one equation.

without loss of generality. Maximizing firms choose to increase the price if  $r_1^* > \max(r_m^*)$ . Under the assumption that  $\eta$  is (cross-sectionally) independently and identically Gumbel distributed, this leads to a multinomial logit model for each horizon  $h$ : (McFadden, 1973, Dubin and McFadden, 1984).

$$\Pr(m_{ij,t+h} = 1, 0, -1 | Z_{ijt}) = \Phi(\gamma_m^h Z_{ijt}) = \frac{e^{\gamma_m^h Z_{ijt}}}{1 + \sum_m e^{\gamma_m^h Z_{ijt}}}. \quad (4)$$

Observe that (3) assumes that coefficients  $\gamma_m^h$  and  $\beta^h$  are specific across outcomes  $m$  and horizons  $h$ . In particular, this flexible specification implies that explanatory variables  $Z_{ij,t}$  can have asymmetric effects at any horizon  $h$  on the probability of price hikes or cuts, so that outcomes  $m$  are not ordered. However, we allow the intensive margin of price changes to vary across horizons, but restrict it to be the same across outcomes.

The second equation (3) is the intensive margin of price adjustment conditional on observing outcome  $m$  in the first step. Consistent estimation of the pass-through coefficients  $\beta^h$  requires additional restrictions because the error term  $u$  might not be independent of all  $\eta_m$ , introducing correlation between explanatory variables and the disturbance term in equations (3), as for instance implied by state-dependent pricing. These restrictions are linearity assumptions on the dependence between the model residuals  $(u, \eta_m)$ . Variant 2 of the Dubin-McFadden approach does not restrict the correlation between the error terms of the selection and linear projection step, but assumes that the conditional expectation of the latter is a linear function of known convolutions of the former, turning the second step estimation into

$$p_{ij,t+h} - p_{ij,t-1+h} = \beta^h X_{ijt} + \underbrace{\lambda_{m^*} \mu(\Pr_{m^*}) + \sum_{m \neq m^*} \lambda_m \left( \mu(\Pr_m) \frac{\Pr_m}{(\Pr_m - 1)} \right)}_{\text{selection bias correction}} m \neq 0 \quad (5)$$

where  $\mu$  are integrals over the individual observation probabilities from the multinomial first step, computed numerically. Note that we exclude unchanged prices from the second step altogether. The aim of the selection bias correction term in (5) is to correct the bias induced by endogenous selection into these non-zero price changes.

## 4 Evidence on extensive and intensive margin of price adjustment

In the rest of this section we present evidence on the extensive margin, and then on the intensive margin of price adjustment. We start describing variables we use in the vectors  $Z$  and  $X$ . First and

foremost, we include the cost shocks, given by  $\phi_{jt-1}^E \Delta \widehat{p}_t^E$ , the energy share times the Danish price of energy projected over oil supply shocks, and  $\phi_{jt-1}^M \Delta p_{jt}^M$ , our measure of firm specific import costs. We also include the price change of competitors at the good-level,  $\Delta p_{-i,jt}$  (constructed using the first two digits of the product in the PPI database, for a total of 74 industries); the controls in firm level cost, namely the change in domestic and imported purchases over the last 3 months, total change in the wage bill; we also control for the 3-month change in firm-level sales. We also include the monthly CPI inflation rate and the change in the Danish nominal effective (trade-weighted) exchange rate (NEER). Moreover, both  $Z$  and  $X$  include good-level dummies for exports, temporary sales, product replacements which we identify as changes in the base price at resampling as well as breaks (see Appendix for details). We also control for the size of the firm by including the log number of employees.

To identify the pass-through coefficients in  $\beta$  non-parametrically, we use exclusion restrictions, by including some variables only in the multinomial logit estimation step, while excluding them from the second linear projection step, guided by theoretical considerations from the literature on state-dependent price setting in multiproduct firms. Therefore, among the regressors  $Z_{ijt}$ , we include the following covariates, which are then excluded from the linear projections in the second step. First, we use the fact that most firms in our sample sell many products whose prices we observe (see section 2.1.1). In line with Alvarez and Lippi (2014) and Bhattarai and Schoenle (2014), we use the fractions of positive and negative price changes within the same firm, excluding the price change of the good we are trying to explain. Note that these fractions may be expected to have different influences on the likelihood of increasing or decreasing prices, and our approach allows for that. We also include the standard deviation of all price changes in the firm in the last 5 years, to take into account that in our sample we have firms with only one reported product, and the average of absolute price changes of goods in the same firm. Second, we include the fraction of positive and negative price changes in the same industry at the 2-digit NACE sector (excluding firm  $j$ ), excluding the  $i$ -th good price. Furthermore, we include month fixed effects (dummies) to let the seasonality in price adjustments help identify the model.

To sum up our main results, we find that shocks to energy costs and the cost of imported inputs significantly affect the probability of changing firm-level prices; however, despite this evidence in support of state-dependent pricing, selection bias, while statistically significant, does not seem to be economically relevant. Moreover, conditional on changing prices, estimated price adjustment is quite different across these two cost shocks, despite the fact that both closely resemble random walks. Adjustment is more immediate on impact but lower over the medium run for the cost of imported inputs than for energy costs. In turn, these differences are accounted for by the fact that

shocks to energy costs have an economy wide impact and diffuse slowly through different sectors in the economy, while import cost shocks are largely idiosyncratic.

## 4.1 Shocks

Here we show the response of the marginal cost variables itself, as well as firm-level cost measures to the shock in figure 5.

### 4.1.1 Import cost shock

Panel 5a shows the response of firm-level import costs, and the right-hand side panel shows the response of total domestic variable costs; the dark and light grey areas indicate 68% and 95% HAC robust confidence bands, where standard errors are clustered at the firm level. Import costs are affected very persistently and their response is very similar to a random walk, although after 12 months it settles on a level slightly below the impact response. Conversely, the response of domestic variable costs, including wages, is not statistically significant. On the basis of this cost dynamics, we would expect under time-dependent, Calvo pricing that firms changing their prices would do so by closely matching the random walk dynamics in import costs. Under state-dependent pricing, firms changing their prices earlier should do so by more than the increase in import costs, because of the selection effect.

### 4.1.2 Energy cost shock

The left-hand side panel shows the response of the cumulated price of energy in Denmark times the firm-level energy share, and the right-hand side panel shows the response of total variable costs (i.e. wages plus domestic and imported intermediates); the dark and light grey areas indicate 68% and 95% HAC robust confidence bands.<sup>13</sup> While the cumulated BH oil supply shocks follow a random walk by construction as their are iid, the left-hand side graph (figure 6a) shows that also the response of the cumulated cost of energy at the firm level is very close to a random walk. The implication is that we can interpret the oil supply shock as a shock to Danish energy costs, with a high persistence similar to the shock to import costs. Thus, on the basis of the energy cost dynamics, we would expect under time-dependent, Calvo pricing that firms changing their prices would do so once and for all, closely matching the random walk behavior of the cost. Under state-dependent pricing, firms changing their prices earlier should do so by more than the increase in costs, because of the selection effect. However, looking at the response of total variable costs in the right-hand

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<sup>13</sup>Standard errors are again clustered at the firm level.

Figure 5: Import cost shock

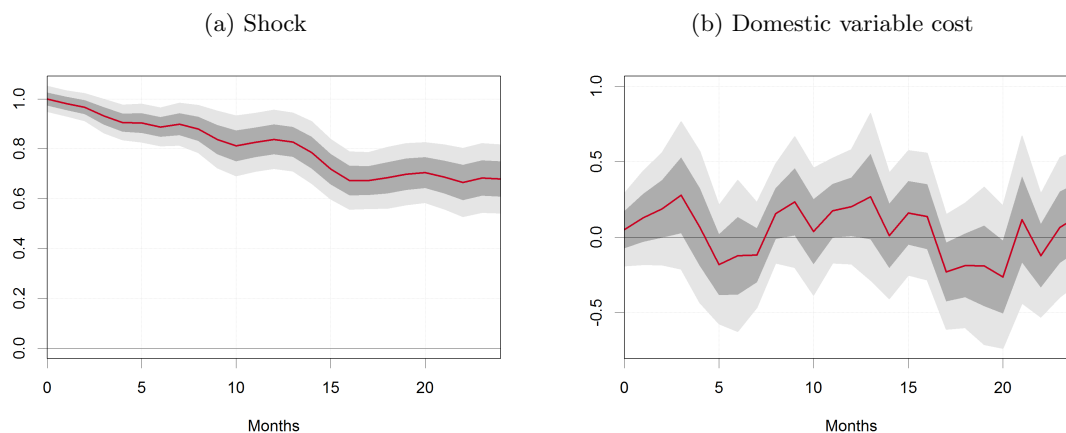
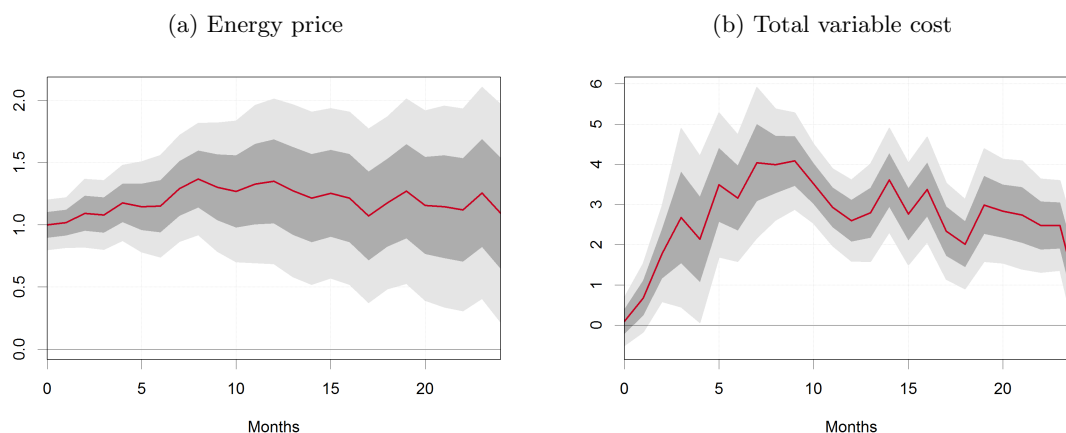


Figure 6: Energy cost shock



Note: Panels (a): Estimated coefficients of firm-level regressions of  $k^{th}$  lead of the cost share variable  $\phi^c$  interacted with the input cost changes  $\Delta P^c$  on the contemporaneous shift-share shock. Panels (b): of regressions of cumulative changes of domestic/total intermediate purchases from VAT data on the same regressors. 95% (68%) confidence bands in (dark) grey.

side graph, it is clear that the shock persistently affects also intermediates and wages, contrary to the import cost shock. This pervasive response of all cost measures is important to keep in mind when interpreting conditional price adjustment to this shock, since it implies that firms in different positions in supply chains are likely to be affected by the shock at different times, depending on the timing of the reaction of their suppliers. As we show below, this "pipeline" pressures are an important feature of the propagation of energy costs to firms' prices and inflation, in addition to the role of nominal and real rigidities.

## 4.2 The extensive margin of price adjustment and synchronization of price changes

As we discussed in the previous section, in the first stage we estimate a multinomial logit model of the following form:

$$\Pr \left( m_{ij,t+h} = 1, 0, -1 \mid Z_{ijt} \right) = \Phi \left( \gamma_m^h Z_{ijt} \right) = \frac{e^{\gamma_m^h Z_{ijt}}}{1 + \sum_m e^{\gamma_m^h Z_{ijt}}},$$

where  $m_{i,j,t+k}$  is an indicator variable for positive, zero, or negative (log) price changes of good  $i$  produced by firm  $j$ , cumulated between time  $t$  and  $t + h$ , with 0 as the base (no price change) category. The logit model has the convenient property that the estimated coefficients take on the natural interpretation of the effect of the explanatory variables on the probability of adjusting prices up or down over taking no action.

To preview our results, the following stand out: First, there is substantial synchronization of price changes within a firm which suggests a key role played by complementarities in the cost of changing prices, especially as the number of goods increases. Specifically, we find that, other things equal, the likelihood of an individual price cut (hike) rises with the number of positive (negative) changes in the other prices within a firm, consistent with common costs of changing prices. Second, there is substantially more synchronization of individual adjustment decisions at the firm level relative to the industry. Third, we find evidence for state-dependent pricing in response not only to the cost shocks of interest (energy costs and the cost of imported inputs), but also more broadly to changes in aggregate inflation and the effective exchange rate, and to competitors' prices

Table 2 shows the results of the multinomial logit model for the horizon  $k = 0$ , where the top panel reports results for price hikes and the bottom panel for price cuts. We report marginal effects on the change in the probability of adjustment, given one-standard-deviation changes around the mean of  $Z_{ij}$ . We report results for all firms and by splitting them in two groups according to the average number of their product (no more than 5 goods, and more than 5 goods, respectively).

A first key finding is that there is evidence of *imperfect* synchronization within the firm. Specifically, the probability of raising (reducing) prices significantly increases with *both* the fraction of positive and negative price changes. The fraction of positive and negative price changes within the firm are especially large and significant across all columns. These results are strongly consistent with synchronization in price changes because of both firm-level shocks to marginal costs, for the fraction of similarly signed price changes, and common costs of changing prices within the firm, for the fraction of opposite-signed price changes. However, the former effect is twice than the latter

for both price increases and decreases. Nevertheless, the effect of price changes of the opposite sign within the firm increases in a statistically significant way with the number of goods produced by firms, in line with models with complementarities in the cost of changing prices.

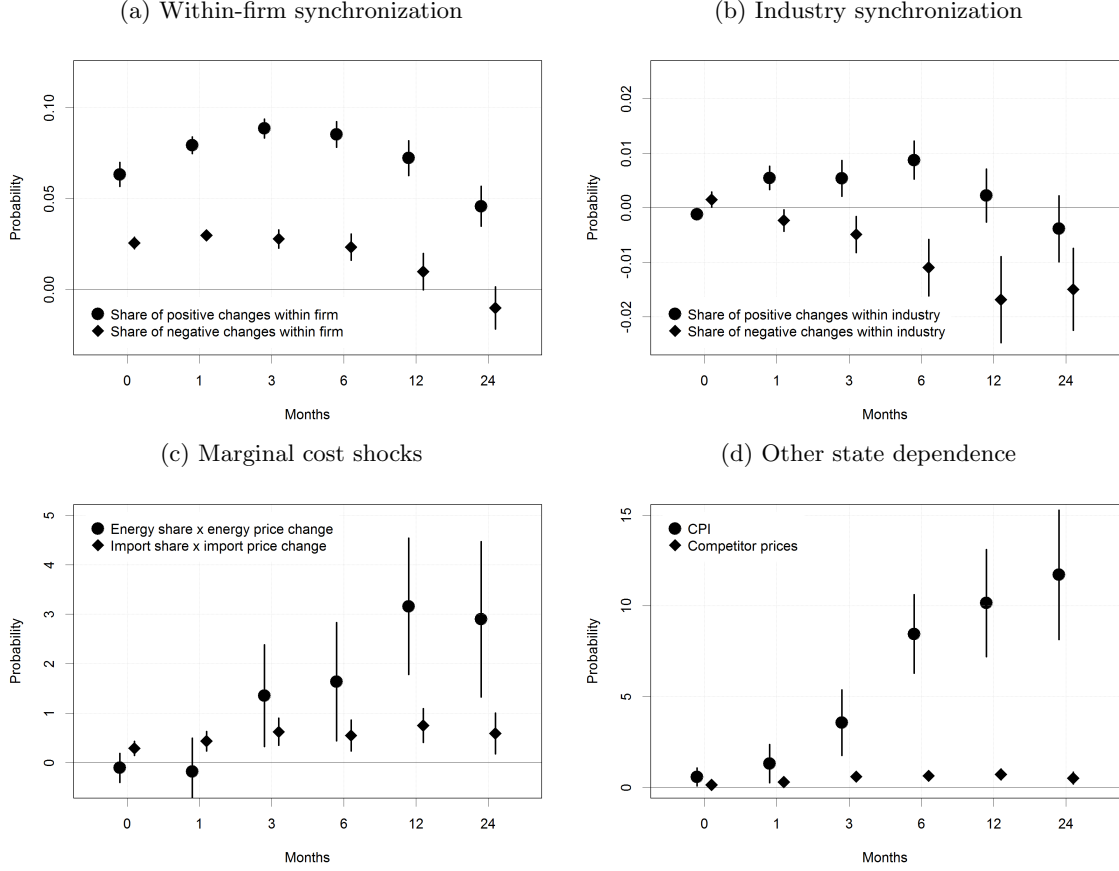
Conversely, we find significant but quantitatively smaller evidence of synchronization at the industry level. The probability of a positive (negative) price change *decreases* with the fraction of negative (positive) price changes in the same industry, but it is in general much less affected by the fraction of price changes with the same sign. This marginal effect is of the opposite sign and an order of magnitude smaller than that for the within-firm fraction of opposite signed price changes. This evidence seems consistent with common shocks to marginal costs across firms rather than strategic complementarities, since it is entirely driven by firms with fewer products. Synchronization in the likelihood of price adjustment across firms is thus decreasing with the number of products, in contrast with synchronization within firms.

The first row of Figure 7 reports marginal effects for the fraction of price changes in the case of price hikes over selected horizons  $k$ . The left-hand side graph shows that both marginal effects within the firm peak between 3-6 months and persist over time; this persistence is in line with the model with multiproduct firms by Bonomo et al. (2019). The marginal effects for the fraction of price changes across firms, shown in the right-hand side graph, display a similar dynamics.

Our second sets of results speaks to a long-debated and important question in macroeconomics, namely whether price setting is time-dependent or state-dependent. On the one hand, we find that there is substantial time-dependence in the probability of changing prices because of calendar effects, as already discussed in Section 2. Specifically, the probability of a price increase is significantly larger in January, April, July and October, than in other months, irrespective of the number of goods produced; conversely, the seasonal pattern for price decreases is not statistically significant.

On the other hand, there is evidence in support of some degree of state-dependent pricing. Consistent with standard menu cost models, not only is the probability of price hikes and cuts increasing in its past volatility. Several time series also significantly and persistently affect the probability of price changes over time. Specifically, a 1% increase (decrease) in energy costs ( $\phi_{jt-1}^E \Delta p_t^E$ ), import costs ( $\phi_{jt-1}^E \Delta p_{jt}^M$ ), the aggregate CPI, the NEER and competitors' prices all significantly raise the likelihood of a price hike (cut), and reduce the probability of a price cut (hike). As shown in the second row of Figure 7, which reports these marginal effects over selected horizons, they build up over time and are very persistent. CPI changes have the larger effect, implying that a 1% rise (fall) at its peak after around 12 months significantly increases the probability of a price hike (cut) by 10% (5.3%). The marginal effects for a 1% rise (fall) in energy and import costs imply a statistically significant increase in the probability of a price hike (cut) of 3% (3.5%) and 1% (0.5%), respectively.

Figure 7: Marginal effects on price increases at selected horizons  $k$



Note: Marginal effects of an increase in the following regressors on the probability of an increase in the price after  $k$  months. The regressors include the normalized share of positive and negative price changes at the firm level, excluding the good (panel a) and the equivalent share at the industry level excluding the firm (panel b). Panel (c) shows the elasticities of the shocks to marginal cost: oil and import price changes. Finally, panel (d) depicts the marginal effects on the probabilities of increasing the price after an increase in the CPI and competitor's prices by 1%.

### 4.3 The intensive margin of price adjustment to cost shocks

In this section we report the results of the estimation in the second stage of the dynamic pass-through conditional on price adjustment. We use local projections à la Jordà (2005), where the dependent variable is the cumulated price change of product  $i$  of firm  $j$  from period  $t$  to  $t+k$ , denoted  $\Delta^k p_{ijt} = p_{i,j,t+k} - p_{ijt}$ , conditional on it being non-zero over this time interval. On the right hand side, the cost shocks are given by  $\phi_{jt-1}^E \Delta p_t^E$  and  $\phi_{jt-1}^M \Delta p_{jt}^M$  (in Danish kroner). We also include as controls the price change of competitors at the good-level,  $\Delta p_{-i,jt}$  (constructed using the first two digits of the product in the PPI database, for a total of 73 industries), and the above mentioned controls for firm-level costs, namely: total change in domestic purchases over



last 3 months, total change in the wage bill, and the change in total (domestic and exported) sales over last three months. We also include the monthly CPI inflation rate and the change in the Danish nominal effective (trade-weighted) exchange rate (NEER). Finally, we again control for the following set of firm/product level time-invariant variables: the number of full-time equivalent employees and the number of products in the year, as well as dummies for price replacement, sales, and export prices and industry fixed effects at the 2-digit level.<sup>14</sup> Finally, in line with our two-stage procedure to take into account selection, following Bourguignon et al. (2007) we include "correction bias" terms from the first stage estimation for each horizon  $t + h$ . Specifically we use variant 2 of the Dubin-McFadden approach, which does not restrict the correlation between the error terms of the selection stage and linear projection stage, but assumes that the conditional expectation of the latter is a linear function of known convolutions of the former. We present first results for the shock to import costs and then for the shock to energy costs; the former is a firm-level shock, while the latter has a much larger common component across firms.

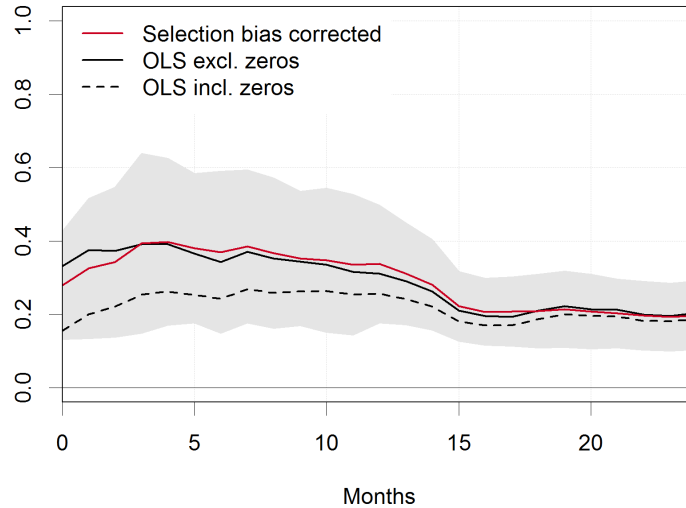
#### 4.3.1 Price pass-through of firm-level import costs

Figure 8 presents three estimates of the price pass-through coefficient on import costs,  $\beta_k^M$ , for each horizon  $k$ . The dashed black line shows OLS estimates of  $\beta_k^M$  including zero and non-zero price changes, while the solid black line also shows OLS estimates of  $\beta_k^M$  including only non-zero price changes; the red line shows the estimates of pass-through coefficients conditional on non-zero price changes from our two-stage procedure, for which the dark and light grey areas indicate 68% and 95% HAC robust confidence bands.<sup>15</sup> The following results emerge. First, the immediate and very persistent increase in import costs brings about a similarly persistent increase in prices, which are significantly affected even after 2 years, with all three estimates basically stable after 12 months. However, OLS pass-through estimates over zero and non-zero price changes display a more gradual adjustment to a (medium-run) elasticity of around 0.2 over horizons after 15 months. The gradual price adjustment in the first 12 months is entirely driven by price stickiness, but the low value of the medium-run elasticity seems to point to an incomplete pass-through of the import cost shock independent of nominal rigidities. This is confirmed by the OLS estimates conditional on non-zero price adjustment, which are very close to those including zeros after 12 months. Second, OLS and bias corrected point estimates are also very similar over all horizons. Therefore, even though we find that the bias correction terms in the second stage are significantly different from zero, the state-dependence we documented in the extensive margin in the first stage does not translate into

<sup>14</sup>Given their computational complexity in the multinomial logit step we do not include firm-level fixed effects; we plan to explore their role in future revisions of the paper.

<sup>15</sup>Standard errors are clustered at the firm level and corrected for first stage uncertainty.

Figure 8: Import price pass-through



Note: Estimated coefficients of a firm-level import price change interacted with the import share of total cost. The solid red line describes the selection-bias corrected estimation proposed in this paper. 95% confidence bands in grey, corrected for first-step uncertainty. The dark blue line represents coefficients estimated by an OLS model where unchanged prices are excluded; the black dashed line includes all observations. Further controls (not reported): Lagged values in the shock, the average price change of competitors excluding the firm, quarterly growth rates of sales and purchases, firm size, dummies for product replacement, sales, and exports, time fixed effects.

an economically large OLS bias.

Next, we try to better understand the reasons why the medium run pass-through seems to be incomplete and much lower than 1. A first reason could be that by using the firm-level import share we are introducing measurement error in the import share at the good level; this could result in downward bias in our estimates. Nevertheless, results do not change when we re-run our estimates aggregating all good price changes at the firm level, arguably reducing measurement error. As shown in the appendix (figure 18a), we still find pretty much the same cost pass-through for firm-level prices as for good-level prices in Figure 8.

A second reason could be the presence of strategic complementarities; given a largely idiosyncratic shock, firms may decide not to completely adjust to it since their competitors are not affected. Moreover, we can expect this effect to be stronger for larger than smaller firms. Indeed, in our local projection estimates we find that good-level competitors' prices,  $\Delta p_{-i,jt}$ , have a positive and statistically significant coefficient across all horizons. This result is consistent with the hypothesis of significant strategic complementarities, but could also just reflect common shocks across firms

that are not perfectly captured by other controls. Therefore, in figure 9 we report conditional OLS pass-through estimates by splitting firms according to size and the number of products. The first row shows good-level price changes of firms with no more than an average of 50 workers on the left-hand side, and with more than 250 workers on average on the right-hand side. The second row shows good-level price changes of firms with no more than an average of 5 goods on the left-hand side, and more than 5 goods on average on the right-hand side. Each graph also shows the cumulated response of competitors' prices including zeros over the different horizons  $k$ ,  $\Delta p_{-i,jt+k}$ , to the import cost shock to firm  $j$ . The figure clearly shows that larger firms with more goods adjust their prices by less, despite the fact that their competitors' prices are in turn more affected by the shock. Pass-through in firms with more goods is about one half of that in firms with fewer goods, and close to the 0.2 estimate in Figure 8 pooling all firms; however the estimated coefficients are still far below 1 even for smaller firms.

Finally, Figure 10 shows that the selection bias is positive only for firms with less than 5 goods; this is consistent with the evidence of stronger synchronization in the extensive margin and thus the multiproduct firm model of Alvarez and Lippi (2014). In this model the larger the number of products, the higher synchronization in price adjustment and the lower the selection bias.

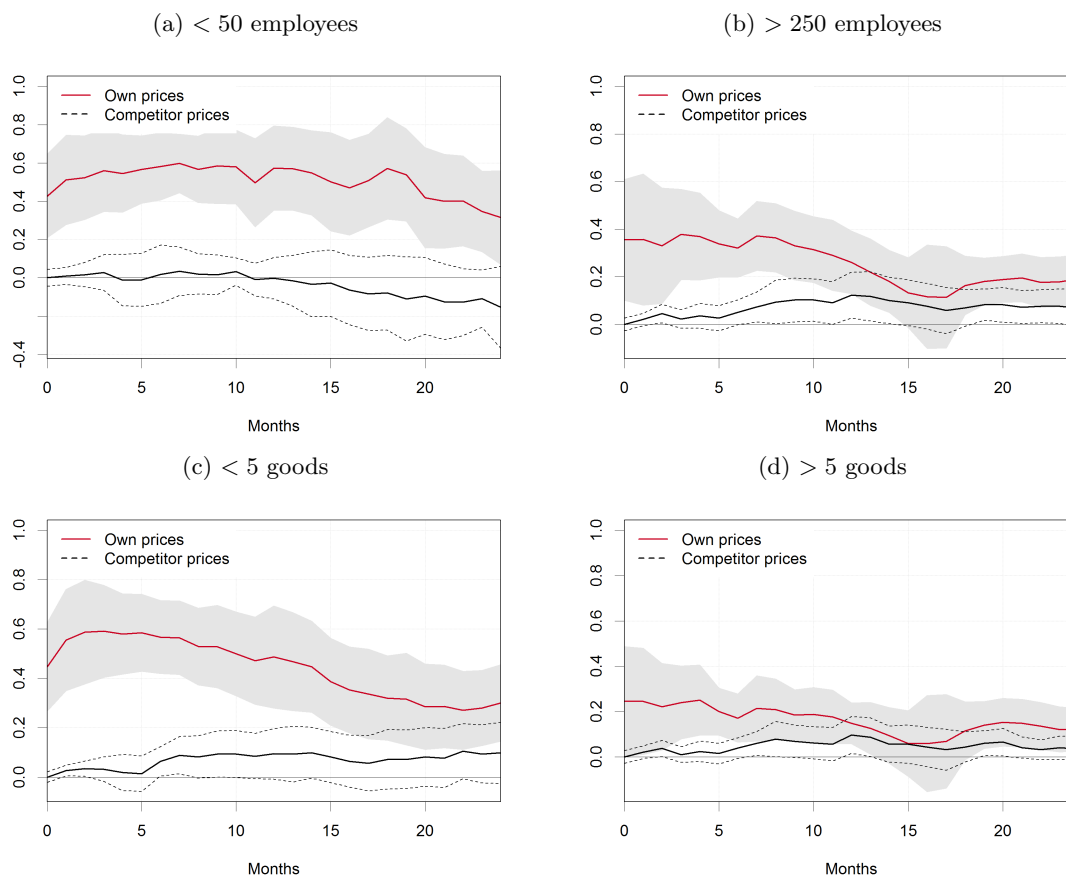
Summing up, we find evidence that in the case of idiosyncratic firm cost shocks, price adjustment is subdued because of nominal rigidities in the short run, and real rigidities in the medium run. Nominal rigidities do not result in a significant selection bias conditional on changing prices, while real rigidities seem to reflect in part by strategic complementarities, with the incomplete medium run pass-through mainly due to the behavior of larger firms.

### 4.3.2 Price pass-through of energy cost shocks

Next, we explore price adjustment to a shock to energy costs due to oil supply shocks. Figure 11 presents as before three estimates of the price pass-through coefficients on energy costs,  $\beta_k^E$ , for each horizon  $k$ . Again, the dashed, black line shows OLS estimates of  $\beta_k^E$  including zero and non-zero price changes, while the solid black line shows OLS estimates of  $\beta_k^E$  including only non-zero price changes; the solid red line shows the estimates of pass-through coefficients conditional on non-zero price changes from our two-stage procedure, for which the dark and light grey areas indicate 68% and 95% HAC robust confidence bands.<sup>16</sup> The following findings stand out. First, despite the immediate and very persistent increase in energy costs in Figure 6, prices increase only very gradually, from a small and statistically insignificant level on impact, to around 0.5 after 6 months, and then peaking at around 0.8-0.9 after 15 months. Remarkably, this is true regardless

<sup>16</sup>Standard errors are clustered at the firm level and corrected for uncertainty due to the first step.

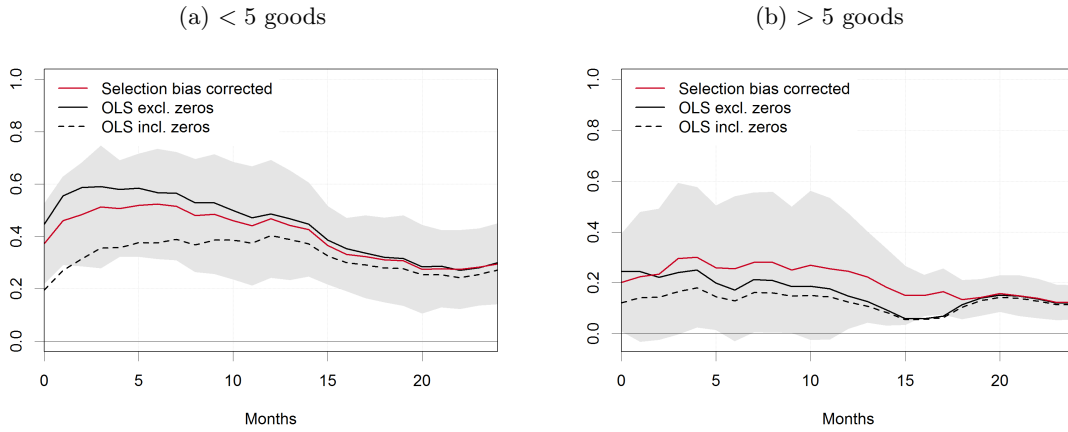
Figure 9: Import cost shock by firm size and number of products



Note: Red solid lines show estimated coefficients of price pass-through in response to a firm-level change in import prices interacted with the import share, conditional on that the price has changed. 95% confidence bands in grey. The black line (and corresponding dashed error bands) show the change in prices of firms competing in the same product sector. Firms are split in groups by the average number of employees or products reported throughout the sample.

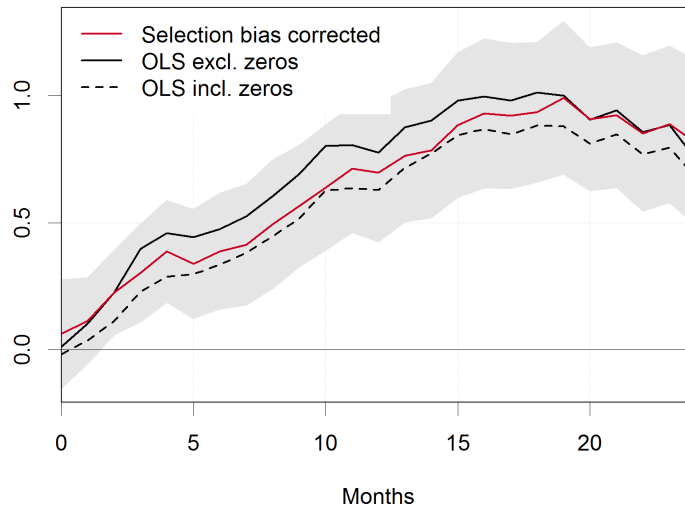
of the exclusion of zero price changes or correcting for selection bias. Therefore, price stickiness seems to play a smaller role in short-run price adjustment in the case of energy costs than import costs. This is consistent with the fact that energy costs have larger effect on the extensive margin of price adjustment in our first stage estimates, as shown above. Second, OLS and bias corrected point estimates are very close to each other, though slightly less than in the case of import costs. Again, the state-dependence we documented in the extensive margin in the first stage does not translate into an economically large OLS bias, contrary to the prediction of standard menu costs models. Finally, we note that the medium run pass-through elasticity is again below 1, even though the oil-driven shock to energy costs persistently affects all variable costs. This is consistent with the presence of "real rigidities" in the intensive margin of price adjustment.

Figure 10: Selection by number of products



Note: Red solid lines show estimated coefficients of price pass-through in response to a firm-level change in import prices interacted with the import share, corrected for the bias induced by endogenous selection. 95% confidence bands in grey. The black solid (dashed) line shows the OLS coefficients excluding (including) unchanged prices. Firms are split in groups by the average number of products reported throughout the sample.

Figure 11: Oil price pass-through



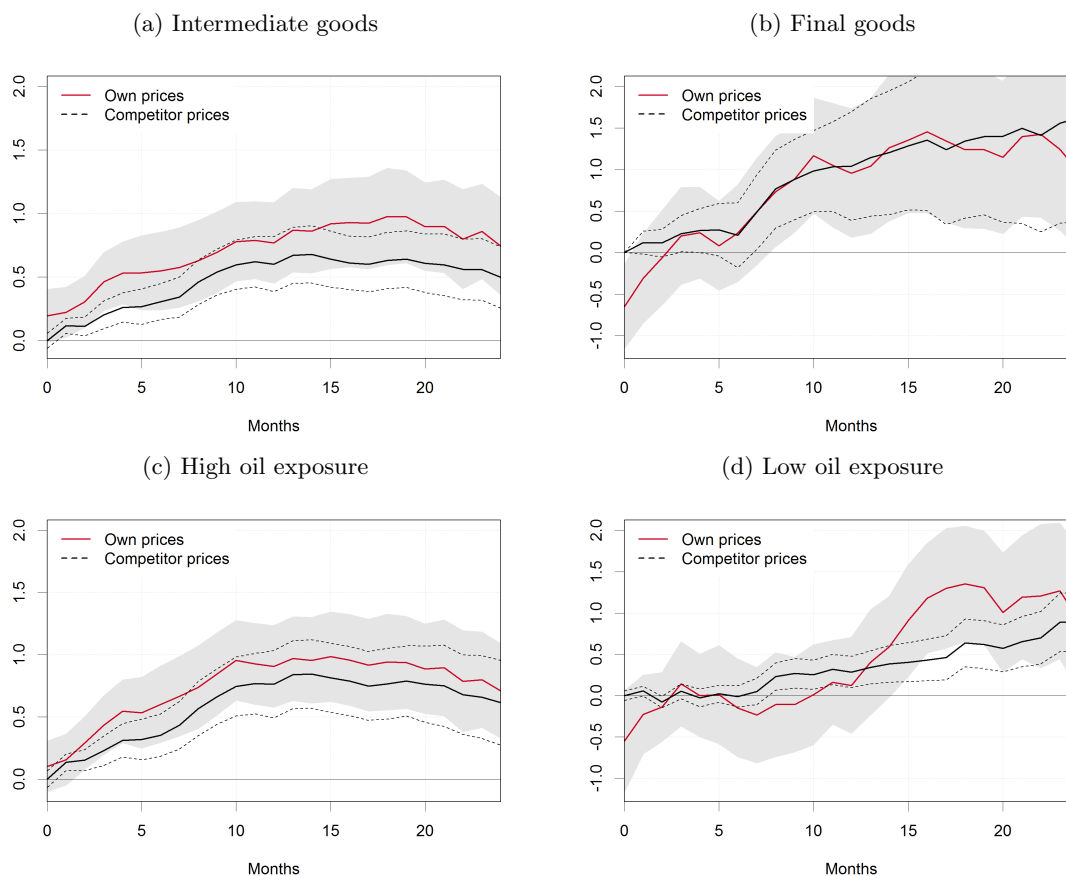
Note: Estimated coefficients of an oil supply shock interacted with the firm-level energy share of total cost. The solid red line describes the selection-bias corrected estimation proposed in this paper. 95% confidence bands in grey, corrected for first-step uncertainty. The dark blue line represents coefficients estimated by an OLS model where unchanged prices are excluded; the black dashed line includes all observations. Further controls (not reported): Lagged values in the shock, the average price change of competitors excluding the firm, quarterly growth rates of sales and purchases, firm size, dummies for product replacement, sales, and exports, time fixed effects.

We next turn to investigating the reasons behind the gradual conditional adjustment in the short run, including the role of strategic complementarities. We first explore the idea that the gradual adjustment may be due to the slow transmission of the shock along the supply chain, with up-stream sectors and sectors more exposed to energy (directly and indirectly) reacting faster than downstream sectors and sectors less exposed to energy. Therefore, in figure 12 we report conditional OLS pass-through estimates by splitting price changes in those of upstream and downstream goods, and in those of sectors with a different exposure to energy (which apart from oil and petroleum products includes electricity and heating). Specifically, the first row shows price changes for intermediate and final goods, on the left-hand side and right-hand side, respectively. The classification of goods is taken from the Danish input-output tables. The second row shows price changes for goods in sectors with overall energy intensity below and above the median, on the left-hand and right-hand side respectively. The overall energy intensity is calculated using detailed input-output tables, taking into account the direct and indirect content of energy through purchases of intermediates. Each graph also shows the cumulated response of competitors' prices including zeros over the different horizons  $k$ ,  $\Delta p_{-i,jt+k}$ , to the shock to energy costs to firm  $j$  (i.e. shocked energy price interacted with the firm-level energy share). The figure clearly shows that prices of intermediates and products with a higher energy intensity respond much faster than those of final goods and products with lower energy intensity. The former's response is positive and statistically significant almost on impact, while the latter's becomes significantly positive well after 6 months (even 12 for low exposure ones). Nevertheless, the response of prices of intermediates and products with a higher energy intensity still builds up over time, peaking only after 12 months at values that are significantly larger than those in the first few months. Moreover, medium run adjustment is very similar across goods, in line with the pervasive effects of the shock on variable costs in Figure 7. Interestingly, competitors' prices display a similar dynamics to that of individual prices across the different types of firms.

Finally, we report results by splitting firms by their size and number of goods, similarly to figure 9 above. The key finding is that larger firms (with more products) tend to have a more gradual adjustment than smaller firms (with fewer products) — even though confidence bands are large. However, given that the shock is fairly common across firms, there is little difference in medium run price adjustment along these dimensions. This result is again consistent with the presence of strategic complementarities, in line with the lower medium run pass-through of the more firm-specific shocks to import costs found above, as prices adjust more when competitors' prices also adjust more.

Summing up our results on the intensive margin, we find evidence of heterogeneous price ad-

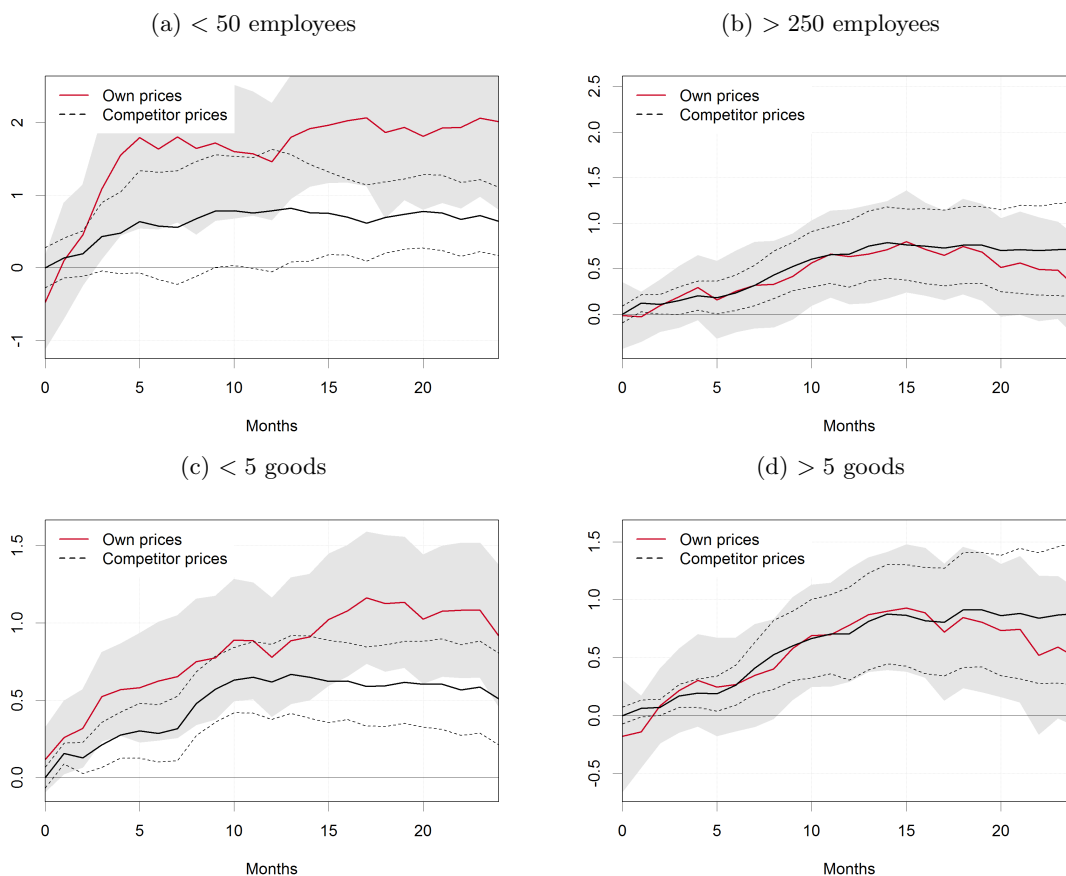
Figure 12: price pass-through by SNA and energy exposure



Note: Red solid lines show estimated coefficients of price pass-through in response to an oil supply shock interacted with the firm-level energy share, conditional on that the price has changed. 95% confidence bands in grey. The black line (and corresponding dashed error bands) show the change in prices of firms competing in the same product sector. Products are split by the UN classification of HS codes into intermediate and consumption goods. In (c) and (d), firms are split at the median based on the energy intensity of the sector they operate in, drawn from input-output tables, i.e. taking into account the indirect exposure to energy through intermediate inputs.

justment to random walk cost shocks that however have a different degree of commonality across firms. In the case of idiosyncratic firm cost shocks, aggregate price adjustment is subdued because of nominal rigidities in the short run, and real rigidities in the medium run. Specifically, strategic complementarities seem important in accounting for the limited medium run response, given that the shock elicits little adjustment in competitors' prices, and the evidence that larger firms react much less to the shock. In the case of similarly persistent energy cost shocks, but more common across firms, we find that aggregate price dynamics in the short-run reflects nominal rigidities but especially the slow diffusion of the shock across sectors differentially affected by it across time. The larger medium run pass-through is also consistent with the pervasive nature of the shock across all

Figure 13: Price pass-through by firm size and number of products



Note: Red solid lines show estimated coefficients of price pass-through in response to a firm-level change in import prices interacted with the import share, conditional on that the price has changed. 95% confidence bands in grey. The black line (and corresponding dashed error bands) show the change in prices of firms competing in the same product sector. Firms are split in groups by the average number of employees or products reported throughout the sample.

firms, whereas we also find some difference across smaller and larger firms only in the first months after the shock. Finally, we also find similarities since for both shocks state-dependence in the extensive margin of adjustment does not result in a significant selection bias conditional on changing prices.



Table 2: Multinomial logit, first stage results

	All	1-5	5+
Marg. effect on probability of price increase			
Fraction of pos. price changes in firm	6.33*** (0.36)	5.22*** (0.21)	7.83*** (0.64)
Fraction of neg. price changes in firm	2.56*** (0.16)	2.19*** (0.11)	2.67*** (0.25)
Fraction of pos. price changes in industry	0.15 (0.14)	0.46*** (0.09)	0.03 (0.13)
Fraction of neg. price changes in industry	-0.12 (0.07)	-0.25 (0.15)	-0.10 (0.06)
Avg. price change in industry, excl. firm	0.14*** (0.04)	0.11** (0.04)	0.11* (0.06)
Energy price change x lagged energy cost share	-0.11 (0.15)	-0.17 (0.17)	0.11 (0.20)
Import price change x lagged import cost share	0.29*** (0.07)	0.50*** (0.19)	0.12* (0.06)
CPI, log difference	0.57* (0.25)	0.55 (0.35)	0.31 (0.33)
Marg. effect on probability of price decrease			
Fraction of pos. price changes in firm	2.36*** (0.19)	2.01*** (0.13)	2.48*** (0.29)
Fraction of neg. price changes in firm	3.95*** (0.27)	3.27*** (0.18)	4.99*** (0.51)
Fraction of pos. price changes in industry	0.02 (0.10)	-0.13 (0.11)	-0.00 (0.14)
Fraction of neg. price changes in industry	0.14 (0.15)	0.59*** (0.12)	0.03 (0.12)
Avg. price change in industry, excl. firm	-0.14*** (0.04)	-0.12*** (0.03)	-0.138** (0.06)
Energy price change x lagged energy cost share	-0.24 (0.14)	-0.18 (0.15)	-0.26 (0.23)
Import price change x lagged import cost share	-0.31*** (0.04)	-0.47*** (0.11)	-0.16** (0.05)
CPI, log difference	-0.82*** (0.29)	-1.08*** (0.41)	-0.38 (0.36)
N	267670	126185	141485
R2	0.40	0.44	0.38

Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Note: Marginal effects (in percentage points) on increasing and decreasing the price relative to not changing the price. The variables of within firm and industry synchronization show the effect of a one standard deviation change of the regressor around its mean; the other variables do so for a 1% change in the input variable. Columns (2) and (3) split the sample along the median number of products. Standard errors in parentheses. The change in firm sales and domestic purchases over the past quarter as well as the change in the hourly wage rate interacted with the labor share account for other firm-level cost components (not reported). Further controls: Log firm size, dummies for product replacement, sales, exported and energy products, the change in the nominal effective exchange rate, month fixed effects.

## 5 Conclusions

This paper studies price adjustment in a novel monthly dataset of prices of multiproduct firms, merged with firm-level balance sheet and cost data. The theoretical literature on price setting has pointed out that the interdependence between the decision to whether or not change prices (the extensive margin) and the actual amount by which prices change (the intensive margin) contributes to determine the real effects of monetary policy. Specifically, in standard menu costs models, firms change those prices that are most misaligned and furthest from their optimal values, resulting in a so-called selection bias that attenuates monetary non-neutrality.

We exploit the richness of our dataset to estimate the pass-through of shocks to firm-level import costs and energy costs (due to oil supply shocks) along extensive and intensive margins, modelling them jointly to address endogenous selection bias due to state-dependent pricing decisions. In our first step, we model the probability of price changes over horizons from 1 to 24 months (extensive margin), by using a flexible multinomial logit model. We find that there is evidence of synchronization of adjustment decisions within firms, especially as the number of goods increases, consistent with models of multiproduct firms. We also find evidence of state dependence as the probability of price adjustment over time is affected by our cost shocks, but also by aggregate inflation and even exchange rates.

Using first-stage estimates to correct for selection bias, we find that state-dependence however does not translate into a large bias in the intensive margin conditional on price adjustment. Moreover, pass-through of energy and import cost shocks is quite heterogeneous across sectors, and firms of different size, respectively. Gradual adjustment to energy costs mainly reflects faster price responses in intermediate sectors and in sectors highly exposed to energy both directly and indirectly. For import-cost shocks, pass-through of larger firms with more products is lower than that of smaller firms with fewer products. Since the latter shocks have a much smaller effect on competitors' prices than shocks to energy costs, our findings are consistent with the presence of strategic complementarities in price setting.

Finally, our results provide micro-based evidence on the debate about the propagation of idiosyncratic and common shocks to aggregate inflation, since firm-specific import cost shocks elicit a faster adjustment than energy cost shocks, whose effects instead build up through the supply chain in line with the pipeline pressure view.

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## A Data

### A.1 Producer price micro data

We use the confidential microdata underlying the Danish producer and import price index for commodities compiled by Statistics Denmark. The raw data covers the time period from January 1993 until June 2017. The producer and import price index for commodities is based on approximately 6'400 prices at the firm-good level per month across 1'050 different commodities, reported by selected producers and importers in Denmark, see also Statistics Denmark (2019). Approximately 3'500 prices are used for calculating the producer price index, approximately 2'900 prices are used for calculating the import price index. The most important firms within selected areas are requested to report prices in order to ensure that the producer and import price index covers at least 70 percent of Danish production and imports.

The population covers all commodities that are imported or produced in Denmark for the domestic market or export, with the exception of some well-defined exemptions. Some commodities are not included because the turnover is too small and some commodities are not included because of the nature of the commodities.

Statistics Denmark undertakes great efforts to adjust for quality changes and product substitutions so that only true price changes are measured. When a product is substituted, Statistics Denmark re-computes the base price, and therefore we are able to identify replacements. They constitute only 0.7 per cent of all prices changes (including zero price changes) and 0.8 per cent of all non-zero price changes. We include these in the baseline results we report, but control for identified product replacements in regressions. Goods are defined relatively narrowly in our dataset, as products are classified using the 8-digit combined nomenclature (CN). The first 6 digits of the CN codes correspond to the World Harmonized System (HS). We address breaks in product classifications by identifying changes in product codes within a firm which do not lead to a change in the price. The vast majority of identified breaks coincides with the months where Statistics Denmark re-defines product categories. The breaks constitutes only 0.04 per cent of all price changes (including zero changes), and *per construction* 0 per cent of all non-zero price changes. Similar to product replacements, we include these incidents in the baseline results we report, but control for identified breaks in regressions.

The prices used for the index are actual prices, which means that the prices must include all possible discounts. Therefore, list prices do not apply unless the prices never include discounts. A distinction is made between the prices of imported commodities and the prices of commodities for the domestic market or the export market:

- Imported commodities: Actual transaction prices (in some cases transfer prices) c.i.f. excluding all duties and taxes on the goods as far as possible on the 15th day of the month. For the firms reporting import prices, we calculate a firm-level import price index using the equally weighted average log differences in each month.
- Danish commodities for the domestic market or export: Actual transaction price (in a few cases transfer prices) ex producer excluding VAT and excise duties as far as possible on the 15th of the month.

One advantage of this data is the relatively long time spans during which we observe uninterrupted price spells, allowing us to study dynamic pass-through at the good level. On average, the price of a good is reported for 115 subsequent months. During the time range we use in our pass-through analysis (2008m1-2017m6), a total of 5'354 product spells (at the firm-good level) can be identified, 79% of which we observe for at least 2 subsequent years. 30% of good id's can even be tracked along the entire sample of 9.5 years. Re-classification of products in January of 2009 (2014) leads to spikes in the exit and entry rate of products of 30% (9%), which we do not link because we do not observe quantities and are therefore unable to compute counterfactually weighted prices. In other months, half of entry and exit of products is driven by firm re-sampling, whereas smaller firms are re-sampled more frequently.

Products reported cover a broad set of goods representative of the Danish economy. The manufacturing sector makes up more than 75% of firms in the data and even more in terms of goods. The second largest industry is wholesale trading. Within manufacturing, machinery, food products, fabricated metal, plastic and computer and electronics are the most commonly found industries. We define sub-markets in terms of products sold at the 2-digit level of HS codes, which results in 74 product categories such as meat, pharmaceutical products, or furniture. Further, we link product identifiers to broad economic categories (BEC) according to UN correspondence tables and report price statistics of frequency and size of price adjustment for each category in table 3.

## A.2 Firm registers

We combine the pricing data with annual firm-level data from Statistics Denmark's accounts statistics for the Danish business sector in the period from 1996 to 2016 (FIRE registers). A firm is identified at the enterprise level, i.e. the legal unit, see also Statistics Denmark (2017). The primary industries, the financial sector and the public sector are excluded.

The share of firm identifiers in the price data we match to accounting statistics lies between 89% (in 2008) and 99% (in 2017).

Table 3: Price change statistics by broad economic category (BEC)

	# unique products	Frequency		Size	
		Mean	Median	Mean	Median
All	5'354	20.6	8.0	7.0	5.0
Consumer goods					
Food	1'081	32.4	15.3	6.9	5.3
Nondurable non-food	462	14.2	6.0	8.4	5.0
Durables	534	11.7	5.3	6.6	4.7
Intermediate goods	1'710	22.1	9.1	7.1	5.1
Energy	85	80.9	96.8	8.8	8.5
Capital goods	1'413	11.9	6.1	6.6	4.5

Note: Summary statistics by broad product categories, 2008-2017. We compute the mean at the product level first, based on which the mean/median is taken across products in the category, classified from HS codes using UN correspondence tables. Frequencies and size of price adjustments are in %.

Income statement items we use include total sales and profits, from which we impute total cost. Firms report the total amount spent on purchasing energy throughout a year. The mean (median) spending on energy as a share of total cost is 1.7% (1.09%). Furthermore, we observe the number of employees in full-time equivalents, firm age (for a subsample of 81% of the firms), as well as expenditure on imported goods. We calculate the latter as a share of approximated total cost: The mean (median) import intensity is 27% (23.1%).

### A.2.1 Monthly sales, purchases, and payrolls

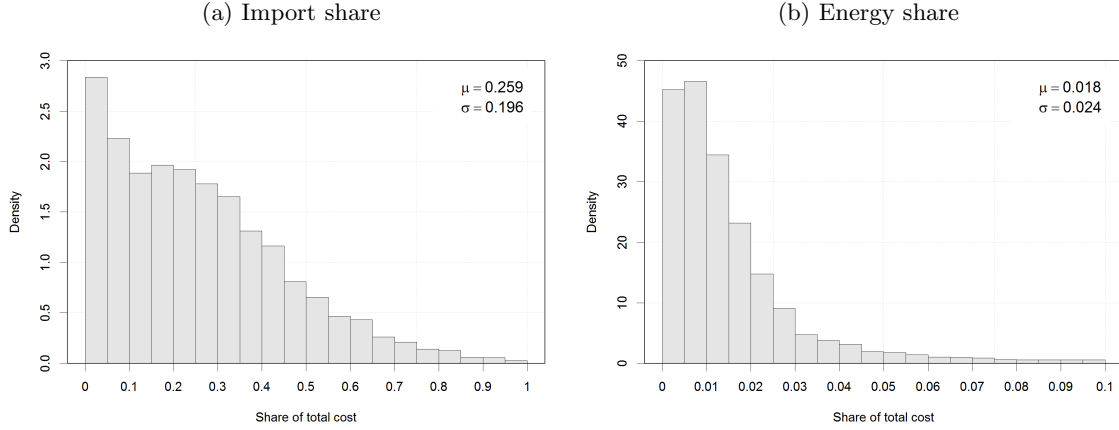
For all firms covered by the Danish VAT system, we have information on purchases and sales, see also Statistics Denmark (2018). The data (referred to by Statistics Denmark by the mnemonic "FIKS") contains information on total sales and total purchases from 2001 to 2017, with the category of imported purchases reported separately starting in 2002.

The monthly frequency of this dataset allows us to leverage the high frequency of the pricing data. However, some firms do not report on a monthly basis, whereas the annual turnover of a firm determines its VAT declaration frequency. The frequency is monthly if the amount exceeds DKK 50 million, quarterly in the interval between DKK 5 million and DKK 50 million, and half-yearly if it is less than DKK 5 million (and above DKK 50,000). Quarterly and semi-annual data are recalculated and spread onto months by Statistics Denmark using information from firms with monthly VAT reporting in the same industry (at the DB-127 level).

Due to the universal nature of the VAT registers, we match more than 99% of good-month



Figure 14: Histograms of cost shares



Note: Imports (from VAT declarations) and energy cost (from annual accounting statistics) divided by total cost at the firm level.

observations for the time range used in this paper (2008m1-2017m6).

Furthermore, we use monthly payrolls from the BFL registers starting in January 2008. Danish firms register hours worked by and total compensation of employees in the tax authority’s *e-Indkomst* with the payment of every remuneration. While the raw registers are matched employer-employee data, we aggregate monthly wage payments and hours to the level of the firm id and link changes to the ppi data. The share of firm identifiers in the price data we match to accounting statistics lies between 89% (in 2008) and 99% (in 2017).

### A.2.2 Cost shares

From these registers, we calculate exposure to cost share in order to estimate elasticities of prices to marginal cost. We calculate lagged import and energy shares by dividing the respective nominal cost by total cost and display their cross-sectional distribution in figure 14.

### A.3 Aggregate energy price shocks

The aggregate shock we consider in this paper is a shock to the price of energy. Changes in the price of energy arguably have a strong demand component, with different implications for the behavior of firms’ prices. We address this issue in two ways: First, we consider oil price changes as a predictor of energy price changes. Since Denmark is a small open economy, changes in domestic demand are unlikely to systematically affect the price of Brent crude oil. Still, domestic and world demand for oil might be correlated, which is why rely on a series of oil supply shocks provided by Baumeister and

Table 4: Elasticities of oil and energy prices with respect to oil supply shocks

	$\Delta P^O$		$\Delta P^E$	
BH oil supply shock	-4.86***	-4.87***	-1.57***	-1.52***
— $t-1$		-0.55		-1.40***
— $t-2$		-0.63		-0.25
— $t-3$		0.39		-0.15
— $t-4$		0.82		0.17
— $t-5$		-0.09		-0.25
— $t-6$		0.15		-0.11
N	114	114	114	114
R2	0.37	0.39	0.16	0.32

Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Note: Dependent variables: Monthly log differences of the price of Brent crude oil ( $\Delta P^O$ ) and the Danish energy price index (incl. oil, electricity and heating) provided by the Danish statistical office ( $\Delta P^E$ ). Regressions on contemporaneous and lagged values of the Baumeister and Hamilton (2019) oil supply shock series. Sample: 2008m1-2017m6.

Hamilton (2019) instead. This paper estimates a VAR with oil prices, production and inventories as well as world industrial production, identified using prior information to distinguish between oil supply and consumption shocks. The prior conjectures that short-run elasticities of production are small. The prior mode is 0.1 (whereas the resulting posterior has a mode of 0.15). Impulse responses show that a one-standard deviation shock to oil production increases the oil price by 3%. When replicating this elasticity for the time period of our sample, we find it to be higher. Table 4 reports the results of a projection of the end-of-month Brent crude oil price on the BH supply series. Baumeister and Hamilton (2019) find that the lion’s share of oil price movements is indeed driven by supply shocks, and that inventories play a minor role in the transmission of this shock, which further motivates our approach.

The cost measure for which we want to estimate the pass-through to producer prices is the price of domestic energy, which apart from oil and petroleum products includes electricity and heating. The index is constructed by the Danish statistical office using a subsample of our PPI data. Its correlation with the oil price changes is 0.46. As the right-hand side columns of table 4 shows, the domestic energy price reacts about a third of how oil prices do on impact, but the loading of the first lag of the BH oil supply shock is positive, indicating that it takes (a relatively short amount of time) for oil shocks to transmit to firm’s energy cost.

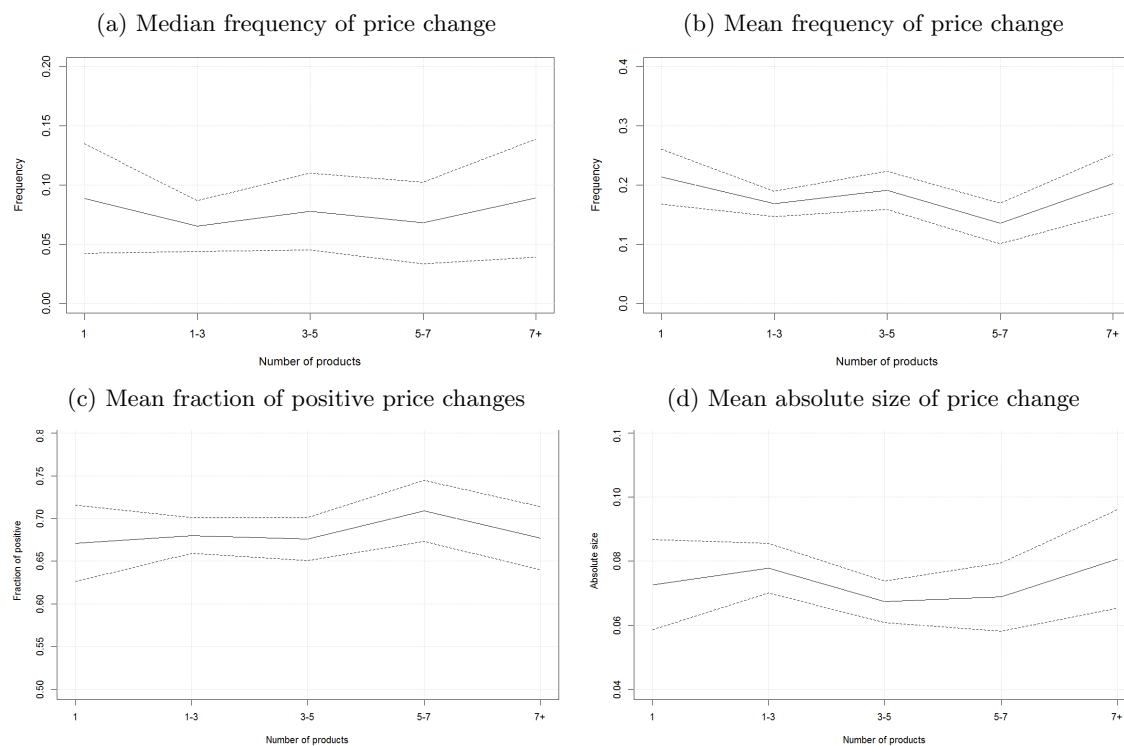
We build the aggregate series as fitted values from the regression  $\hat{\Delta P}_t^E = \beta_0 + \beta_1 BH_t$  (i.e. column 3), normalized to have the variance of the original series  $\Delta P_t^E$ . This way, we can interpret

the size of the shock as an exogenous shock to world supply of oil equivalent to a 2.4% increase in the oil price and a 1% increase in domestic energy cost.

## B Multiproduct firms

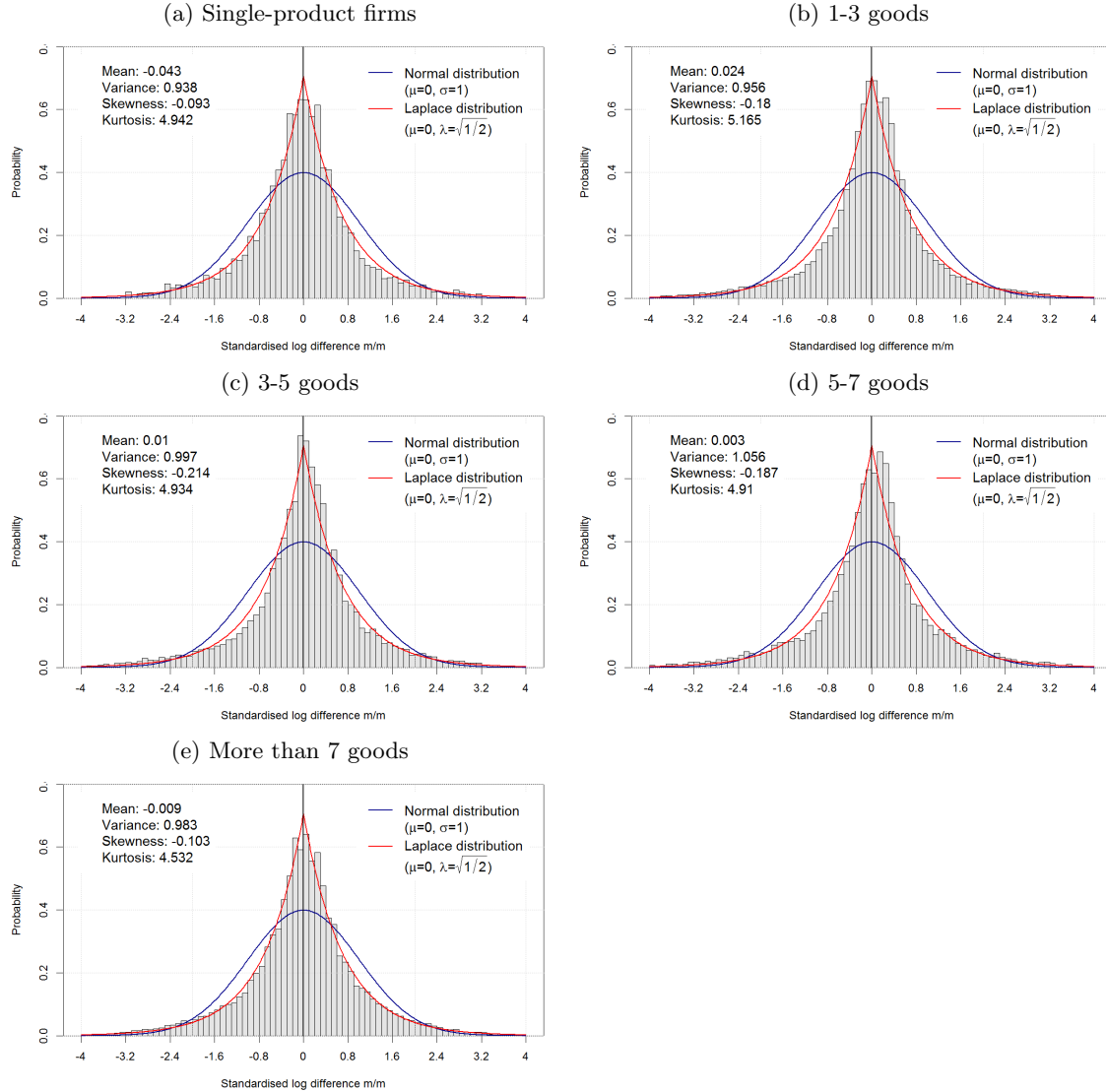
This section replicates figures from Bhattarai and Schoenle (2014) and Alvarez et al. (2016) for firms producing different number of products.

Figure 15: Price adjustments by number of products



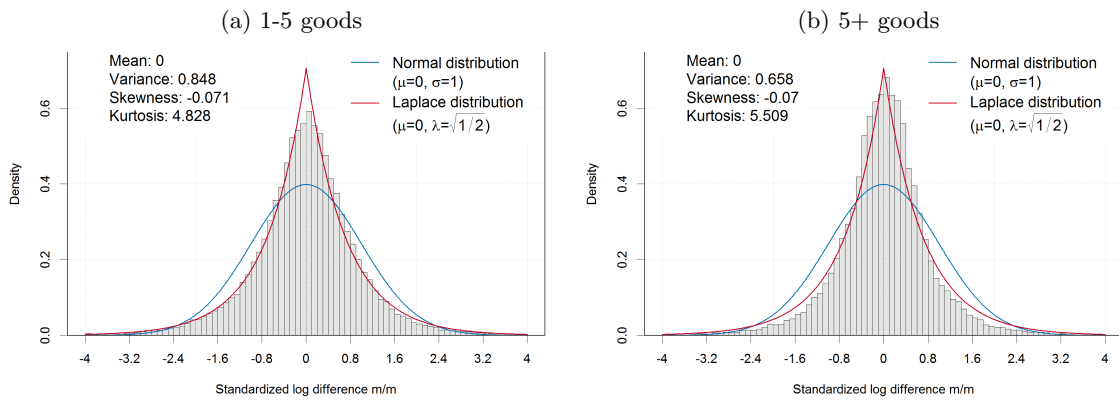
Note: We first calculate mean frequencies and size of non-zero price changes at the good level, and aggregate over all products in firms of a particular bin. Firms are binned according to the average number of products reported throughout the sample

Figure 16: Histogram of price changes by number of products



Note: We disregard zero-price changes and price changes that are smaller than 0.1%, which might be measurement error. We then normalize price changes at the level of the 2-digit HS code by subtracting the mean and dividing by the standard deviation within the sector. The plots show the histograms of these normalized price changes, as well as superimposed normal and Laplace distributions with unit variance. Firms are binned according to the average number of products reported throughout the sample.

Figure 17: Histogram of variable cost changes by number of products



Note: Variable cost is measured as the monthly sum of intermediate purchases (both domestic and imports) and payroll. We exclude zero-cost changes and cost changes that are smaller than 0.1%, which might be measurement error. We then normalize price changes at the level of the 2-digit HS code by subtracting the mean and dividing by the standard deviation within the sector. The plots show the histograms of these normalized price changes, as well as superimposed normal and Laplace distributions with unit variance. Firms are binned according to the average number of products reported throughout the sample.

## C Econometrics

### C.1 Dubin and McFadden (1984) linearity assumption

In particular, we use Dubin and McFadden (1984)'s normalized linearity assumption

$$E(u|\eta_m) = \sigma \sum_m r_m^* \eta_m^*$$

to finish...

### C.2 Standard error estimation in selection-biased corrected pass-through regression

to do...

## D Synchronization

Table 5: Multinomial logit, price synchronization

	All	1-3	3-5	5-7	7+
Marg. effect on probability of decrease					
Fraction of pos. price changes in firm	2.44*** (0.00)	1.85*** (0.03)	2.26*** (0.00)	2.12*** (0.05)	2.76*** (0.06)
Fraction of neg. price changes in firm	3.95*** (0.00)	2.57*** (0.03)	3.87*** (0.00)	4.01*** (0.05)	5.26*** (0.05)
Fraction of pos. price changes in industry	0.14*** (0.03)	0.038 (0.07)	-0.117 (0.06)	0.040 (0.07)	0.22*** (0.05)
Fraction of neg. price changes in industry	0.41*** (0.02)	0.62*** (0.07)	0.58*** (0.05)	0.44*** (0.06)	0.26*** (0.05)
Avg. price change in firm, excl. good	-0.09*** (0.00)	-0.066 (0.04)	-0.04*** (0.00)	-0.038 (0.04)	-0.261** (0.09)
Avg. abs. price change in firm, excl. good	0.02*** (0.00)	-0.004 (0.04)	0.04*** (0.00)	0.041 (0.04)	-0.079 (0.08)
Avg. price change in industry, excl. firm	-0.25*** (0.03)	-0.22*** (0.05)	-0.098 (0.06)	-0.137* (0.07)	-0.34*** (0.07)
CPI, log difference	-0.460** (0.14)	-0.536* (0.26)	-0.627* (0.28)	-0.612* (0.29)	0.170 (0.30)
Marg. effect on probability of increase					
Fraction of pos. price changes in firm	6.18*** (0.00)	4.37*** (0.03)	5.96*** (0.00)	6.31*** (0.05)	8.30*** (0.05)
Fraction of neg. price changes in firm	2.79*** (0.00)	2.07*** (0.03)	2.59*** (0.00)	2.65*** (0.06)	2.81*** (0.06)
Fraction of pos. price changes in industry	0.35*** (0.03)	0.46*** (0.07)	0.51*** (0.07)	0.214** (0.08)	0.26*** (0.06)
Fraction of neg. price changes in industry	0.044 (0.02)	0.053 (0.08)	-0.125* (0.06)	-0.134 (0.07)	0.153* (0.06)
Avg. price change in firm, excl. good	0.10*** (0.00)	0.095* (0.04)	0.04*** (0.00)	-0.015 (0.05)	0.38*** (0.09)
Avg. abs. price change in firm, excl. good	-0.02*** (0.00)	0.005 (0.05)	0.05*** (0.00)	0.015 (0.05)	-0.251** (0.09)
Avg. price change in industry, excl. firm	0.27*** (0.03)	0.24*** (0.05)	0.154** (0.05)	0.101 (0.06)	0.38*** (0.06)
CPI, log difference	0.69*** (0.16)	0.695* (0.28)	0.960** (0.31)	0.261 (0.32)	0.427 (0.33)
N	599310	157652	151956	112730	161751
R2	0.404	0.445	0.437	0.473	0.369

Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

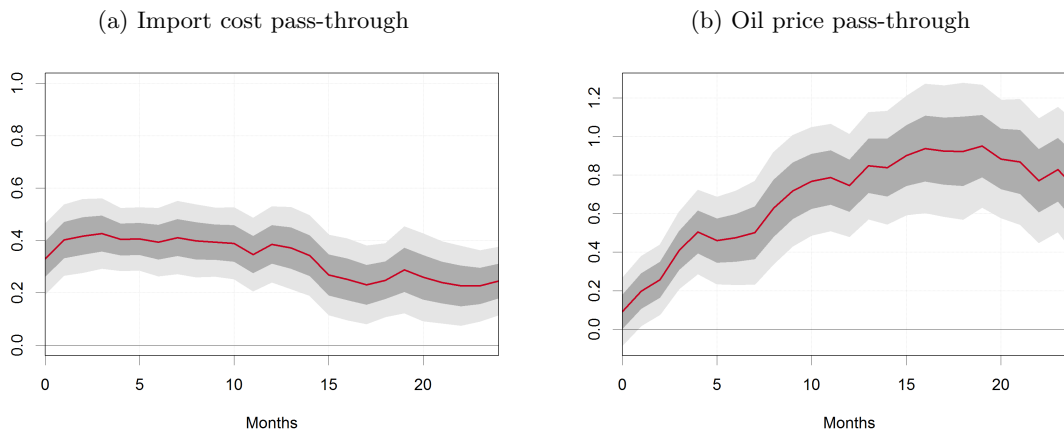
Note: Marginal effects (in percentage points) of a one standard deviation change in the regressor from the mean on the probability of increasing and decreasing the price relative to not changing the price. Exception: 1% in CPI inflation. Standard errors in parentheses. Further controls (not reported): Firm size, dummies for product replacement, sales, and exports, month fixed effects.

## E Robustness

### E.1 Firm-level pass-through regressions

We re-run local projections at the firm-level, rather than at the good-level. We calculate a geometric average of firm-level price changes between  $t$  and  $t + k$ , conditional on the price of the good having changed.

Figure 18: Pass-through estimations at firm level



Note: Estimated coefficients of a firm-level import price change interacted with the import share of total cost, and equivalent for energy. The left-hand side variable is the average change of prices within a firm over  $k$  months, given that the price of the underlying product has changed. The coefficients are estimated using OLS. 95% (68%) confidence bands in (dark) grey.