Price Rigidity within Firm-to-firm Relationships

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Abstract

We study the origins of price rigidity within firm-to-firm relationships. At the product level, we document significant heterogeneity in the frequency of price changes from a given supplier to different clients. Our results show that, for a given product, supplier-buyer characteristics drive an important fraction ($\approx 40\%$) of the heterogeneity in price adjustment among firms. We then show that suppliers with a higher market share in their clients' purchases are more likely to adjust prices in the face of oil price shocks. The effect is stronger for positive than negative shocks, highlighting the role of bilateral market power in price-setting behavior. We rationalize our results in a model with menu costs, non-constant demand elasticities, and market power within supplier-client relationships.

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1 Introduction

Sectoral heterogeneity in price stickiness is crucial in amplifying the degree of monetary non-neutrality of monetary policy (see, for example, Basu, 1995; Nakamura and Steinsson, 2010; Pasten, Schoenle, and Weber, 2020). Recent studies have demonstrated the relevance of the interplay between price stickiness' heterogeneity and both the structure intersectoral linkages (see, for example, Pasten, Schoenle, and Weber, 2020; Rubbo, 2023) and within-sector market structure (see, for example, Mongey, 2021). However, as these two features have been studied in isolation, little is known about their joint role in determining price-setting behavior within firm-to-firm relationships. Bringing these two features—firm-to-firm linkages and market structure—together can provide a better understanding of the micro origins of price rigidity in the context of supply chains, which can help discipline structural models of price stickiness and assess the pass-through of shocks such as the large observed swings in oil prices during 2020-2023.

In this paper, we study the sources of price rigidity within firm-to-firm relationships. We particularly focus on the role that firm linkages and bilateral market shares play in shaping granular price adjustment decisions. For doing so, we use Chilean transaction-level micro data on prices at the seller-buyer-variety level. Our analysis proceeds in several steps. First, we document the aggregate evolution of price adjustment frequency, with particular attention to the shift observed during the COVID-19 pandemic. Next, we decompose the variance in price adjustment frequency across supplier, product, client, and supplier-client-specific effects, revealing that a substantial share of this variation is attributable to supplier-client characteristics.

We then conduct a regression analysis of price adjustment frequency on observable firm characteristics, including firm size, market share, and bilateral market importance. We find that, while firm size plays a role, the bilateral market share—the importance of a supplier in a buyerâs total purchases—emerges as a key predictor of how frequently prices are adjusted, especially during the COVID-19 period, a period characterized by an

endogenous increase in the frequency of price adjustments (Cavallo, Lippi, and Miyahara, 2024, e.g,). This finding suggests that price rigidity is not merely a product of firm-level attributes but is strongly influenced by the specific structure of inter-firm linkages.

While the frequency of price changes is important, it is ultimately the conditional response of prices to shocks that matters most for macroeconomic outcomes. Consistent with recent work by Cavallo, Lippi, and Miyahara (2024) and Blanco et al. (2024), our results indicate that the frequency of price adjustment shapes the pass-through of shocks. However, in contrast to previous studies, we show that an important driver of the frequency of price adjustment depends on supplier-client relationship characteristics. Specifically, we analyze the transmission of oil price shocks within our dataset. We find that suppliers are more likely to adjust the prices they charge to buyers for whom they represent a larger share of inputs, underscoring the importance of relationship-specific dependency in determining the extent of price pass-through.

In our final section, we discuss the implications for economic theory. We propose a simple model in the spirit of Gopinath and Itskhoki (2010) (i.e., menu costs and non-constant demand elasticity) but adapted to supplier-client relationships affected by oil price shocks. In the model, suppliers with higher market share in their buyer purchases of that input, face a more inelastic demand, which increases their probability of adjusting prices in the face of oil price shocks. Consistent with our evidence, these suppliers also change prices more, conditional on adjusting.

Our paper contributes to the literature studying sources of price setting using micro-data (e.g., Nakamura and Steinsson, 2008; Goldberg and Hellerstein, 2011; Bhattarai and Schoenle, 2014; Amiti, Itskhoki, and Konings, 2019; Hong et al., 2023). Our contribution is to provide a comprehensive description of the determinants of firm-to-firm price rigidity, which jointly considers supplier, client, and supplier-client characteristics. Our results complement the evidence documented in Goldberg and Hellerstein (2011) on the role of large firms' price setting. In addition, building on Pasten, Schoenle, and Weber (2020) we

highlight the significant degree of heterogeneity in price rigidity among supplier-client industry pairs.

Our work also contributes to the literature on multi-sector models with sticky prices and input-output networks (e.g., Pasten, Schoenle, and Weber, 2020; La'O and Tahbaz-Salehi, 2022; Rubbo, 2023; Afrouzi and Bhattarai, 2023; Ghassibe, 2021). While these studies emphasize sectoral heterogeneity in price stickiness, a simple implication of our results is that, sectoral-level price stickiness ought to properly weight the fact that suppliers in a given sector can display different degree of price stickiness to firms in other sectors. The interaction between firm-to-firm level stickiness and networks can generate non-linear effects that aggregate in non-trivial ways.

More specifically, our findings challenge the traditional view that network structure and price rigidity can be considered in isolation. Instead, our results suggest that the rigidity of prices within a sector or firm is inherently linked to the structure of its network, particularly in the face of granular shocksâsuch as an energy transition shockâthat disproportionately affect specific firms.

Our results relate to the recent literature that emphasizes the role of market structure in shaping the extensive margin of price adjustment to shocks and the degree of monetary non-neutrality, as in Mongey (2021). Our findings complement Mongey's by documenting that a two-sided market structure is important in shaping supplier-client price setting dynamics.[1]

Finally, our work contributes to the literature investigating the role of supplier-client relationships in shaping firms pass-through of shocks (e.g., Alviarez et al., 2023; Fontaine, Martin, and Mejean, 2020). Our key contribution is that we focus on the extensive margin of price adjustments in a context of menu costs to adjusting prices.

[1] Alviarez et al. (2023) document the importance of two-sided market power in the exporter-importer relationship. On the other hand, Burstein, Cravino, and Rojas (2024) use similar data to study the determinants of price dispersion, at a point in time, within a supplier to its different customers. The authors document that observables, such as product type and buyer-seller characteristics explain only a small fraction of the observed dispersion. However, the authors focus on the price level or magnitude of price change, while our focus is on the extensive margin of price setting.

2 Data

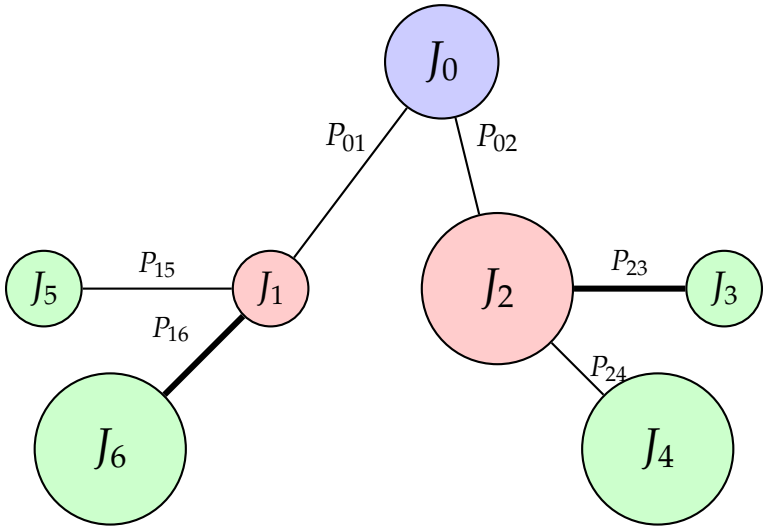
Our data source consists of a comprehensive firm-to-firm transaction-level dataset, encompassing the universe of firms in Chile. Formal businesses in Chile must submit their electronic receipts to the Chilean Internal Revenue Service (SII) compliance with regulatory mandates since 2018. The main variables we have access to are firms' unique tax identification numbers of both the supplier and the buyer, the date of the transaction, the total value of the transaction, the price per *unit*, the type of product involved in the transaction, and the location of the establishment.[2]

Figure 1 describes our data within firm-to-firm transactions. For simplicity, let us assume that each firm supplies one type of product. In the graph, we observe supplier J_0 selling its product to two different buyers, J_1 and J_2. The price charged to each buyer can differ and it is represented by P_{01} and P_{02}. The size of the node indicates the size of the firm and the thickness of the arrow represents the characteristics that are specific to the supplier-buyer pair (e.g., intensity, frequency, duration of the relationship). For example, supplier J_1 is a small supplier selling to a small buyer (J_5) and a large buyer J_6. The thicker arrow from J_1 to J_6 indicates a stronger relationship between supplier 1 and buyer 6, compared to supplier 1 and buyer 5.[3]

[2]To secure the privacy of workers and firms, the CBC mandates that the development, extraction, and publication of the results should not allow the identification, directly or indirectly, of natural or legal persons. All the analysis was implemented by the authors and did not involve nor compromise the IRS.

[3]Mongey (2021) emphasizes the role of firm-level market share in driving price adjustments. Alviarez et al. (2023) show how supplier and buyer market share within firm-to-firm relationships shapes price adjustments. Heise (2024) documents the importance of the age of the relationship between a supplier and a buyer in shaping shocks' transmission to prices.

Figure 1: Network graph of an oil supplier (J_0).



Note: network graph of a supplier J_0. J_1 and J_2 are customers of J_0, while J_3 and J_4 are customers of J_2, and J_5 and J_6 are customers of J_1.

Our dataset is enriched with balance sheet information for both sellers and clients involved in the transactions. This supplementary data includes total sales, employment figures, industry classifications, and input purchases, among other variables.

Table 1 shows the descriptive statistics of annual sales, numbers of customers, and numbers of product subclasses sold. Subclasses are defined by the 173 aggregated product categories used by the National Institute of Statistics in Chile. The median firm in the sample displays annual sales of 250 CLP millions, 3.3 customers, and 1.3 product subclasses.

Table 1: Descriptive statistics (supplier characteristics)

	Mean	Std. Dev.	p10	p25	p50	p75	p90	Obs.
Average sales (CLP millions)	7,050	133,640	35.19	87.13	250.45	882.1	3,657	15,568
Number of customers	45.5	966.7	1.0	1.3	3.3	11.4	35.5	15,568
Number of products sold	2.4	3.2	1.0	1.0	1.3	2.5	4.8	15,568

Consistent with the literature (e.g., Gabaix, 2011), the distribution of firm size is highly skewed. There is a long right tail with a handful of very large firms, implying an average sales that is almost thirty times larger than the median sales. A similar pattern is observed

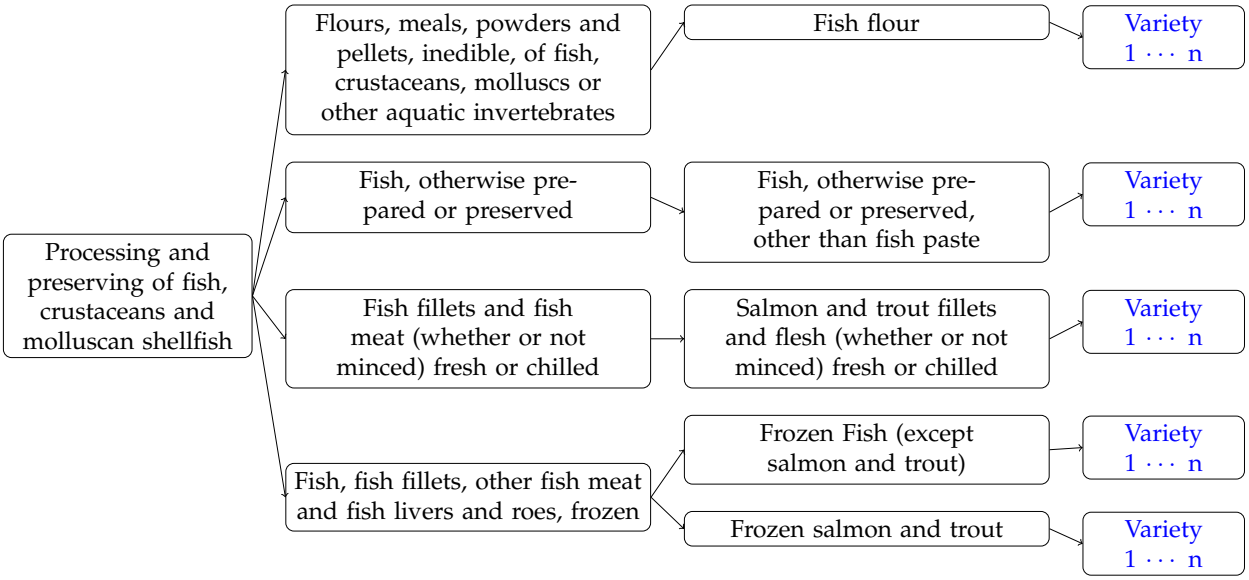
for the number of customers each supplier has. While the median firm has 3.3 customers, the average firm sells inputs to 45.5 customers. The average number of product subclasses sold by a supplier is 2.4, while the median is 1.3.

Here we describe the degree of disaggregation of transaction price data. One complication is that the reported information on the type of product or service traded among firms is self-reported and not always using standardized product definitions. For example, there might be two firms selling the same type of milk but one could report it as "two percent milk 1 liter" and the other as "2% milk 1lt". In this example, one would identify these as two different products. To overcome this limitation, we follow the methodology for data cleaning and processing outlined by Acevedo et al. (2023).

Acevedo et al. (2023) classify individual transactions from the firm-to-firm dataset into standardized product categories, such as the Individual Consumption Classification by Purpose (ICCP). This approach employs a supervised machine learning model on product descriptions and other observables, enabling the assignment of each transaction to a product category contained within the Consumer Price Index (CPI). Figure 2 provides an example of the level of granularity in our data. At the product class we have processing and preserving of fish, crustaceans and molluscan shellfish. These classes are further split into subclasses (e.g., fish, otherwise prepared or preserved), products (e.g., fish flour), and varieties (e.g., tuna fish flour).

To maintain a focus on significant and recurrent transactions, we have applied the following criteria to the dataset. Varieties included in our analysis are restricted to those associated with products in the official Consumer Price Index (CPI) and Producer Price Index (PPI) baskets. Moreover, each variety must be present in the dataset at least 24 times across any supplier to be considered in our analysis, allowing us to exclude sporadic or non-representative transactions. Price changes ($d \log P$) at the extreme percentiles (1 and 99) have been excluded to eliminate outliers and ensure a robust examination of price movements.

Figure 2: Example of granularity in price data: Classes, Subclasses, Products, and varieties



2.1 Validating price data with official data

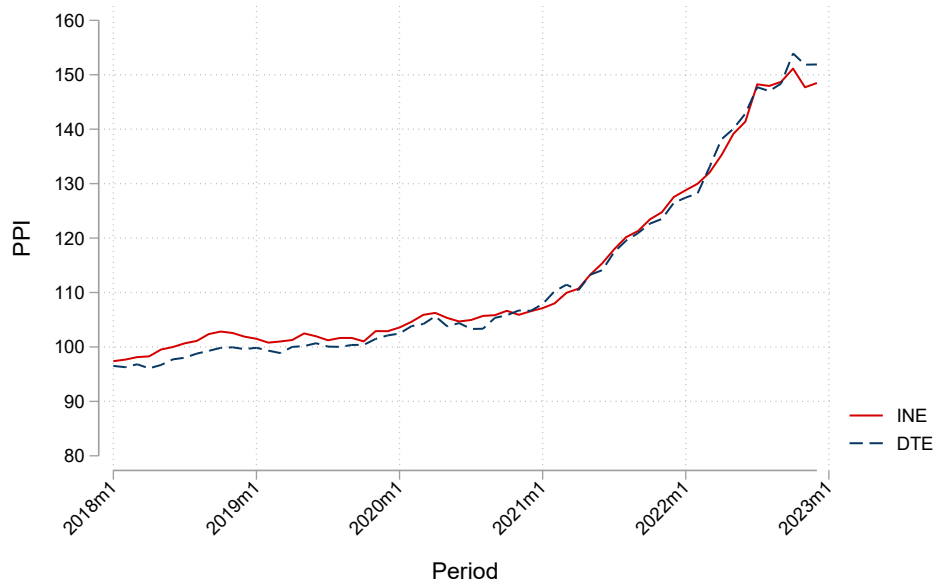
We now proceed to describe the validity and representativeness of our data. We compare the evolution of the official producer price index (PPI^{INE}) and the index we construct using our series of prices (PPI^{c}), which we define as

$$PPI_t^c = \sum_s \omega_s^{INE} P_{st},$$

where ω_s^{INE} is the PPI weight of subclass s in the official PPI by the INE, and P_{st} is the price of the subclass s at time t. We have access to daily transaction-level data which we aggregate to monthly prices following the methodology used by the National Institute of Statistics in Chile (INE). In particular, the subclass price is a geometric average of firm-level prices selling the subclass during a given month.

Figure 3 depicts the evolution of the official PPI index and the PPI we construct. We are able to successfully replicate the evolution of the official PPI. There are some small differences in levels but the correlation between the series is 0.99.

Figure 3: Producer Price Index (PPI): official vs constructed



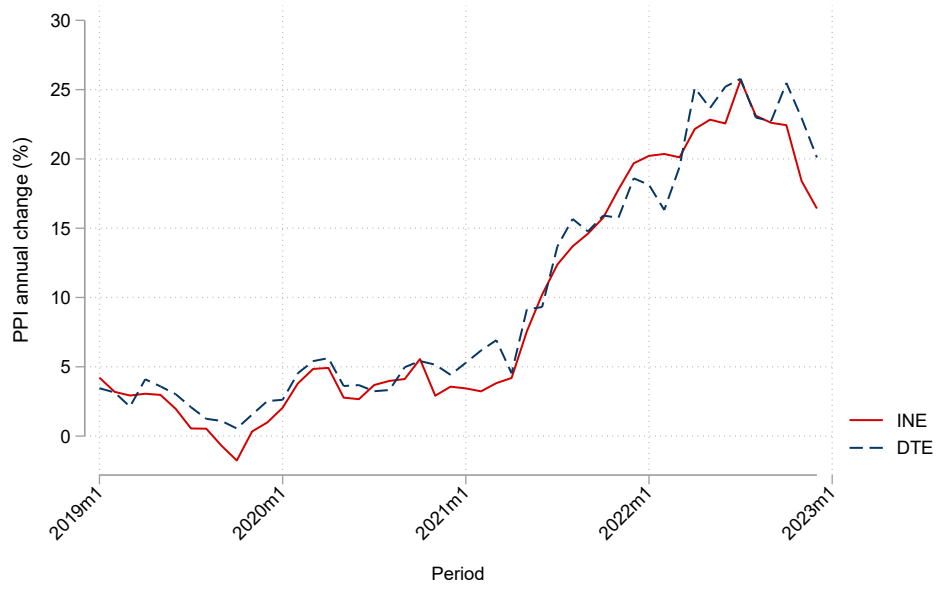
Note: The sum of weights is 0.97 of 100, and there are 165 of 173 products

The next Figure shows the implied annual percent change in prices (inflation). Our annual inflation measure is defined as

$$\pi_t^{PPI} = \sum_s \omega_s^{INE}(p_{st} - p_{st-1})$$

where p_{st} denotes the log of P_{st}. Figure 4 shows the evolution of PPI's official annual inflation and our proxy of it. We can trace down actual PPI inflation quite well. The correlation between the series is 0.98.

Figure 4: Annual PPI inflation: official vs constructed



Note: The sum of weights is 0.97 of 100, and there are 165 of 173 products

3 Facts on the Frequency and magnitude of price changes

In this section, we provide facts on firms' frequency price adjustment. We take advantage of the granularity of our data and present results at the supplier-client-variety level. Throughout the paper, we also provide facts at the supplier-client-subclass level. We aggregate slightly to show that our results are not driven by potentially mischaracterized varieties of a same product.

We define the frequency of price adjustment f_{ijv} as

$$f_{ijv} = \frac{\sum_{t=1}^{T_{ijv}} \mathbf{1}(|\Delta p_{ijvt}| > 0.005)}{T_{ijv}}, \tag{1}$$

in which $\mathbf{1}(|\Delta p_{ijvt}| > 0.005)$ is an indicator variable that takes the value of one if the price charged by supplier i to client j for variety v changed by more than 0.5%, and zero otherwise.[4] Here we have two options in defining Δp_{ijvt}. The first definition considers

[4]We use different thresholds and the results stay the same.

non-consecutive transactions, implying $\Delta p_{ijvt} = p_{ijv,t} - p_{ijv,t-\gamma_{ijt}}$, where γ_{ijvt} represents the time span between transactions. The second definition only considers the triplets ijv that display transactions in consecutive months. Therefore, in this case, we have $\Delta p_{ijvt} = p_{ijv,t} - p_{ijv,t-1}$. Throughout the paper, we focus on the first definition. In the Appendix, we use the second definition. All the main results stay the same.

In Table 2 we present the main descriptive statistics for the frequency of price change in our PPI data. The average price frequency is 0.34 and the median is 0.25. Note that the average frequency of price change at the supplier level is similar to that at the supplier-client-variety level.[5] As we will show next, these averages mask important heterogeneity in price adjustment at the supplier-client-variety level. The average frequency of price adjustment of 0.34 is somewhat larger than the average values in previous papers. However, as we show below, an important driver of this fact is the rise in the frequency of price changes during COVID-19.

Table 2: Frequency price change at supplier f_i and supplier-client-variety level f_{ijv}

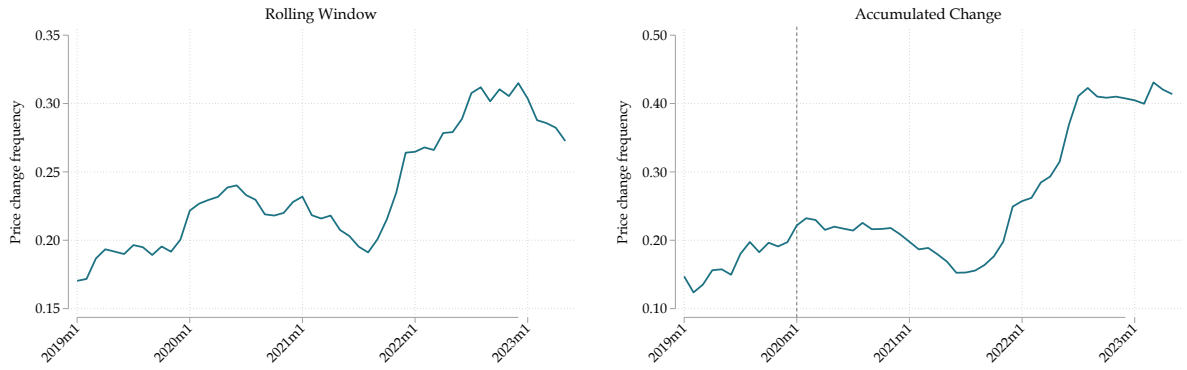
	Mean	SD	P10	P25	P50	P75	P90	N
f_i	0.34	0.28	0.05	0.13	0.25	0.50	0.84	15,568
dp_i	0.13	0.19	0.05	0.07	0.10	0.14	0.21	15,568
f_{ijv}	0.33	0.29	0.00	0.10	0.25	0.50	0.77	10,348,986
dp_{ijv}	0.31	0.26	0.00	0.12	0.25	0.45	0.71	8,014,515

Note: We measure the frequency price change f_{ijv} according to Equation (1). There are 15,568 suppliers in our dataset and 10,348,986 supplier-client-variety triplets.

Consistent with the findings in Blanco et al. (2024) and Cavallo, Lippi, and Miyahara (2024), the frequency of price adjustment significantly increased during COVID-19. In Figure 5 we observe that before COVID-19, prices adjusted 20% of the time. However, during COVID-19, the accumulated frequency of price changes (panel b), doubled to 40%.

[5] At the supplier level, we construct a simple supplier's price index averaging across varieties and buyers.

Figure 5: Absolute frequency change of prices



To assess the role of the extensive margin of price changes in inflation we perform the following decomposition, motivated by Klenow and Willis (2016). Let us define annual PPI inflation as follows:

$$\pi_t^{PPI} = \sum_s \omega_s (p_{st} - p_{st-1}),$$

$$\pi_t^{PPI} = \underbrace{\left(\sum_s \sum_t \omega_s I_{st} \right)}_{\text{Fraction of changing prices}} \underbrace{\left(\frac{\sum_s \sum_t \omega_s (p_{st} - p_{st-1})}{\sum_s \sum_t \omega_s I_{st}} \right)}_{\text{Average change, conditional on a change}},$$

in which I_{st} is an indicator variable that takes the value of one when the price of product s changed more than a threshold ϵ ($abs(p_{st} - p_{st-1}) > \epsilon$), and zero otherwise. We use a threshold rather than zero as we construct p_{st} using geometric averages, meaning that if only one firm selling product s changes the price, I_{st} would equal one for all firms.

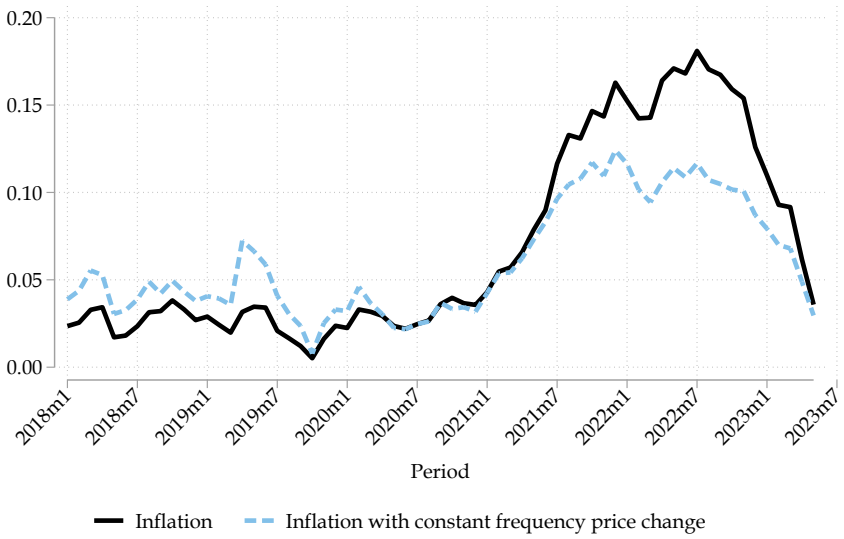
For the decomposition we follow Blanco et al. (2024). We compare the evolution of inflation against the inflation that would prevail if $\sum_s \sum_t \omega_s I_{st}$, the fraction of products changing prices stays constant and equal to its time average $\overline{\sum_s \sum_t \omega_s I_{st}}$. Specifically, we have

$$\overline{\pi}_t^{PPI} = \overline{\left(\sum_s \sum_t \omega_s I_{st} \right)} \left(\frac{\sum_s \sum_t \omega_s (p_{st} - p_{st-1})}{\sum_s \sum_t \omega_s I_{st}} \right),$$

We analyze annual inflation and use $\epsilon = 5\%$. Figure 6, shows that frequency price change played an important role in driving inflation during the 2021-2023 period. If firms

maintained the historical average frequency of price change, peak inflation during 2023 would have been 40% lower. These results are consistent with those in González and Rojas (2023), who using a slightly different approach, show that monthly inflation is largely driven by the extensive margin of prices.[6]

Figure 6: Decomposition of annual PPI inflation: the role of the extensive margin of price adjustment



Note: Frequency of price change is defined for annual index changes greater than 5%.

4 Firm-to-firm facts

Our goal is to understand the role of supplier-client relationships in shaping the frequency of price adjustments. Fontaine, Martin, and Mejean (2020), Dhyne, Kikkawa, and Magerman (2022) and Alviarez et al. (2023) have emphasized the importance of match-specific characteristics in shaping the heterogeneity in the level of prices. In the presence of menu costs, market structure can also affect the frequency at which prices adjust (e.g., Gopinath and Itskhoki, 2010; Mongey, 2021). Hence, we study how price rigidity at the relationship

[6] In their analysis, the authors consider a price change only when the specific variety, within the product subclass, changed more than 10%, monthly.

level depends on bilateral market shares, among other supplier-client characteristics.

We measure the suppliers and buyers market shares following Alviarez et al. (2023). In particular, the supplier's market share as follows

$$s_{ijst} = \frac{p_{ijst}q_{ijst}}{\sum_{k \in Z_j} p_{kjst}q_{kjst}},$$

where $p_{ijst}q_{ijst}$ represents the sales of product subclass s from seller i to buyer j at time t. The denominator $\sum_{k \in Z_j} p_{kjst}q_{kjst}$ represents the purchases of input s made by buyer j from all possible suppliers $k \in Z_j$, with Z_j describing the set of suppliers of firm j.

We also measure the market share of a given buyer j in the sales of a supplier i (x_{ijst}) as follows

$$x_{ijst} = \frac{q_{ijst}}{\sum_{k \in Z_i} q_{ikst}}.$$

Our regressions also control for the number (#) of transactions we observe between a given seller-buyer and the length of relationship between the pair.[7]

Table 3 provides descriptive statistics of the bilateral market shares. Both measures, especially the buyer's bilateral market share are highly skewed. The median relationship displays a supplier market share of 1, meaning that for a given buyer, the supplier of that product is the only supplier. The average supplier, however, has a market share of 68% of the buyer's purchases of that product.

Table 3: Descriptive Statistics Bilateral Market Power (ijs level)

	Mean	Std. Dev.	p10	p25	Median	p75	p90	Obs.
s_{ijs}	0.686	0.399	0.031	0.251	1	1	1	1,698,557
x_{ijs}	0.039	0.157	0	0	0	0.002	0.004	1,698,557

Note: We measure the bilateral market shares at the supplier-client-subclass level ijs. There are 15,568 suppliers in our dataset, 10,348,986 supplier-client-variety triplets, and 1,698,557 supplier-client-subclass triplets. The numbers in this table consider the period average for each supplier-client-subclass triplet.

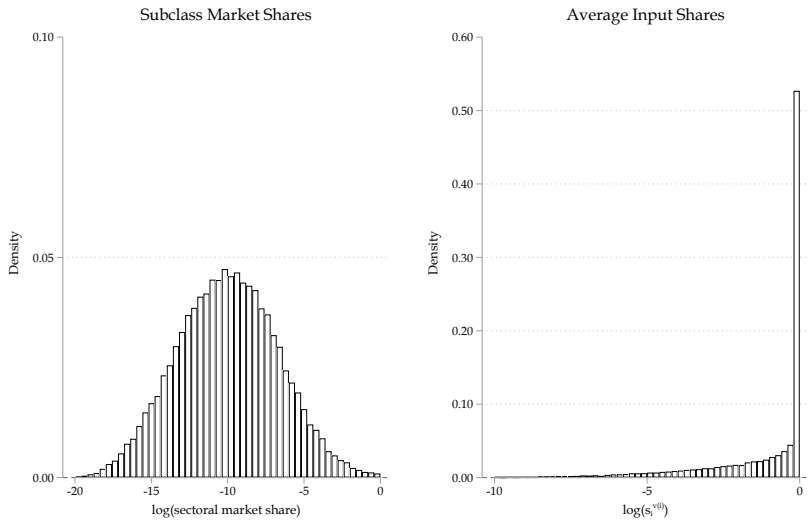
The buyers' market share, in terms of quantities, displays an average of 3.9% and a

[7] Heise (2024) documents a positive relationship between the price pass-through (intensive margin) in exporter-importer relationships and the age of that relationship. The author explains this pattern in a model displaying customer relationship in firm-to-firm relationships.

median of 0.01%. Only at the top 5% and 1% of buyers' market shares, we observe a bilateral market share of 0.19 and 1, respectively. Therefore, unlike the supplier market share, most buyers are atomistic, with the exception of the 99th percentile, in which one particular buyer purchases all the production of a given seller-variety pair.

Figure 7 depicts in panel a) the distribution of firm-level market share at the subclass level.[8] In panel b), we plot the distribution of a given supplier's average bilateral market share with all his clients s_{ijv}. There are clear differences between the distribution of total market shares and the supplier-client market shares. There is significantly more variation in the former, while the latter is characterized by a large mass of suppliers holding a large share of clients' purchases. This result is consistent with that documented in Dhyne, Kikkawa, and Magerman (2022), except that our finer level of disaggregation uncovers even larger differences between the two measures.

Figure 7: Subclass share comparison



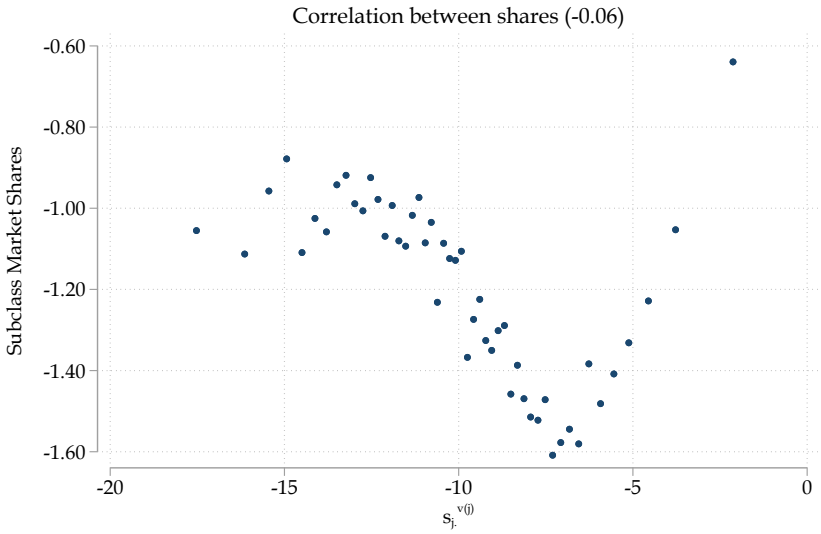
Note: This figure plots the histogram of the logarithm of firms' product market shares, panel a), and the logarithm of the average product market share within supplier-client relationships, panel b). Both measures are averaged over time to obtain one measure per supplier or per supplier-client pair.

In Figure 8 we show the U-shaped relationship between the two measures of market

[8]This is simply the total sales of seller i of subclass s over the total amount of sales of product s in the economy.

shares. The overall correlation is -0.06. For a significant part of the distribution of firm-level size, we observe that being a large firm in the market is associated with smaller market power at the supplier-client level. For suppliers with a very large average bilateral market share we do observe a positive relationship between the overall market share and the average bilateral market share.

Figure 8: Subclass share correlation



Note: This figure plots the binscatter plot between product market shares and the average product market share within supplier-client relationships.

5 Price rigidity within supplier-client relationships

In this section, we analyze the determinants of price rigidity from a granular perspective. The literature has emphasized the role of product characteristics (homogeneous vs non-homogeneous goods) and the role of firm characteristics (e.g., number of goods, market share). Instead, we focus on understanding the role of firm-to-firm characteristics in shaping the extensive margin of price adjustments.

We follow the approach in Fontaine, Martin, and Mejean (2020) and Alviarez et al. (2023) to investigate the role of supplier characteristics, buyer characteristics, product

characteristics, or match-specific (supplier-buyer) characteristics in driving the dynamics of price adjustment.

The regression we estimate is

$$y_{ijvt} = \alpha + \beta X_{ijvt} + FE_i + FE_j + FE_{vt} + \epsilon_{ijvt}, \tag{2}$$

in which y_{ijvt} can be the logarithm of the price p_{ijvt}, the price adjustment dummy that takes a value of one when the price adjustment is larger than a threshold of 0.5% ($\mathbf{1}(|\Delta p_{ijvt}| > 0.005)$) and zero otherwise, or the magnitude of price adjustment Δp_{ijvt}, conditional on adjusting. The variables X_{ijv} are seller-buyer-variety/subclass match-specific controls described in the previous section. We consider a seller fixed-effects FE_i, a buyer fixed-effect FE_j, a variety/subclass-time FE_{vt} fixed-effect, and a residual ϵ_{ijvt} that accounts for supplier-client-variety characteristics that vary overtime.

Table 4 reports the decomposition for different dependent variables. Column 1 considers the log of the price as the dependent variable. Similar to Fontaine, Martin, and Mejean (2020) and Alviarez et al. (2023), Panel A of column 1 shows that most of the dispersion in the price charged by a supplier to different customers is driven by the supplier (47%) and product-time fixed effects (46%). In Panel B, within a given supplier and a specific product, 74% of the variation in the price charged to a given buyer is driven by supplier-client characteristics.[9] In terms of observables, similar to the results in Alviarez et al. (2023), we observe that suppliers with larger bilateral market shares charge higher prices. In contrast, buyers with a higher market share in the buyers' sales receive lower prices.

Columns 2 to 4 provide our main result. In Panel A of column 2 we observe that the extensive margin of price adjustment is driven mainly by the supplier-client characteristics E_{ijvt} (42%). Within a supplier and a variety, the importance of match-specific characteristics is even larger (97%). Bilateral market shares, from the buyer and the supplier, are

[9]Similar results hold if we measure prices at the subclass level in Table 6 of our Appendix.

Table 4: Price and Frequency Price Change Decomposition

	(1) $\ln P$	(2) f_{ijvt}	(3) $f_{ijvt} > 0$	(4) $f_{ijvt} < 0$
s_{ijst}	0.016***	0.028***	0.025***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
x_{ijst}	-0.062***	-0.024***	-0.028***	0.004
	(0.005)	(0.004)	(0.003)	(0.003)
Ln(Num Transactions)	0.009***	0.014***	0.013***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Rel Duration)	-0.008***	-0.004***	-0.004***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Panel A. Overall price dispersion				
Controls	0.0000	0.0010	0.0008	0.0003
FE_i	0.4956	0.1762	0.0689	0.1091
FE_j	0.0300	0.0096	0.004	0.0081
FE_{vt}	0.4455	0.3860	0.469	0.2242
E_{ijvt}	0.0289	0.4272	0.4573	0.6583
Panel B. Within seller-product dispersion				
Controls	0.0036	0.0021	0.0014	0.0004
FE_j	0.2583	0.0224	0.0091	0.0127
E_{ijvt}	0.7381	0.9755	0.9895	0.9869
Obs.	87549155	87549155	87549155	87549155
Adj. R^2	0.970	0.556	0.525	0.316

Note: This table regresses the logarithm of prices (columns 1 and 2) and a dummy for price adjustment $\mathbf{1}(|\Delta p_{ijvt}| > 0.005)$ (columns 3 and 4). The controls are those in Equation (2). The decomposition in panel B subtracts from the dependent variable the estimated fixed effect of the supplier (E_i) and the variety-time fixed-effect E_{vt}.

also important in driving the extensive margin of price adjustment. Suppliers with higher market share change prices more frequently, while buyers with higher market share receive less frequent price changes.

In columns 3 and 4 we also report the results for the frequency of price increases and price decreases. Suppliers with higher market shares tend to change prices more frequently, mainly driven by price increases (column 3) rather than price declines (column 4). In terms of the buyers' market share, we observe that all the effect of buyers' market

shares is explained by the lower frequency of price increases that these buyers face from their suppliers. These results complement those in Alviarez et al. (2023) and Fontaine, Martin, and Mejean (2020) in two dimensions. First, our results concern with domestic firm-to-firm relationships. Second, we show that, not only the level or magnitude of price changes but, the extensive margin of price adjustment is shaped by supplier-client characteristics.

5.1 Frequency price change during COVID-19

Here we study how supplier-client-variety characteristics might have differential effects over different periods of time. In particular, we study the role of bilateral market shares in accounting for the rise in the frequency of price changes during COVID-19 (see Figure 5). We estimate the following regression

$$f_{ijv}^{T} = \alpha + \beta X_{ijv} + FE_i + FE_j + FE_v + \epsilon_{ijv}$$

where f_{ijv}^{T} is the average frequency price change from Equation 1 for a particular subperiod T. Table 5 reports in columns 1-3 the relationship between the frequency of price adjustment and relationship observables for the period 2018m1-2020m2. In columns 4-6, we report the results for the period 2020m3-2023m6. To avoid composition effects due to entry and exit of firms or relationships, our pre-COVID-19 and post-COVID-19 displays the same set of supplier-client-variety relationships.

The results show that the supplier market shares played a relevant role during the COVID-19 period but not for the pre-COVID-19 period. Indeed, the variable s_{ijs} is only statistically significant during the COVID-19 period (column 5). Column 6 shows that the interaction between bilateral market shares and supplier size is also positive, indicating that supplier size reinforced the role of bilateral market shares.

Our results complement the results in Karadi et al. (2024), Cavallo, Lippi, and Miya-

Table 5: Supplier market shares and COVID-19

	(1)	(2)	(3)	(4)	(5)	(6)
s_{ijs}		0.001	0.012		0.006***	-0.048***
		(0.001)	(0.010)		(0.001)	(0.011)
$s_{ijs} \times \log sales_i$			-0.000			0.002***
			(0.000)			(0.000)
			(0.001)			(0.002)
Period	Pre-2020	Pre-2020	Pre-2020	Post-2020	Post-2020	Post-2020
N (triplets ijv)	1,483,494	1,483,494	1,483,494	1,483,494	1,483,494	1,483,494
Adjusted R^2	0.564	0.565	0.565	0.543	0.546	0.546

Note: This table regresses the frequency price adjustment f_{ijv} for the pre-COVID-19 period (columns 1-3) and the COVID-19 period (columns 4-6) against the supplier, client, product-time fixed effects and observables at the relationship level: bilateral market shares, number of transactions, and relationship duration, as well as interactions between seller and buyer size (logarithm of sales) and bilateral market shares.

hara (2024), and Blanco et al. (2024). The frequency price change increased during COVID-19 and increased more for relationships in which suppliers displayed higher bilateral market shares.

6 Price adjustments to oil price shocks

So far, we have provided evidence of unconditional price changes and how these changes relate to firm-to-firm relationships. Here we study the importance of the nature of firm-to-firm relationships in the transmission of oil price shocks along the production network in terms of the extensive margin and extensive margin of price adjustment.[10]

[10] Lafrogne-Joussier, Martin, and Méjean (2023) also study the pass-through of oil price shocks focusing on the intensive margin of adjustment at the firm level. The authors show that the pass-through is larger for larger firms, indicating oligopoly power in pricing decisions as in Atkeson and Burstein (2008).

6.1 The extensive margin adjustment

For the extensive margin of price adjustment we follow Karadi, Schoenle, and Wursten (2024) and estimate the following regression

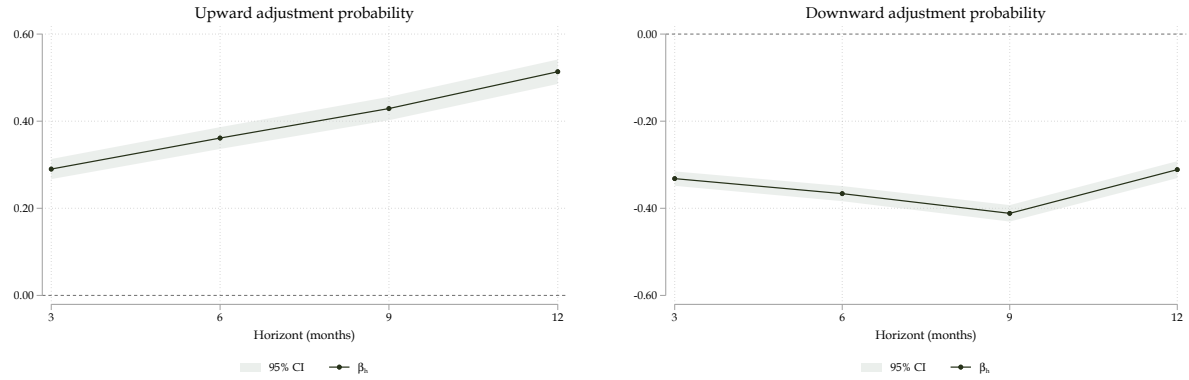
$$I^{+,-}_{ijs,t+h} = \alpha_i + \alpha_j + \alpha_s + \beta_h \Delta \log \hat{P}^{oil}_{it} + \phi_h (\Delta \log \hat{P}^{oil}_{it} \times Z_{ij}) + \gamma_h X_{ij} + \psi w_t + \epsilon_{ijs}, \quad (3)$$

where $^{+,-}_{ijs,t+h}$ is a dummy variable that takes the value of one if the log change of prices from period $t+h$ compared to period $t-1$ for supplier i, selling product v to customer j, changed. The variable $\Delta \log \hat{P}^{oil}_{it}$ is the change in the log of oil price that is relevant for supplier i. This is, we measure the exposure of supplier i to oil as an input. We consider supplier i's direct and indirect usage of oil via the firm-to-firm network (see, for example Minton and Wheaton, 2023). We instrument the change in oil prices using the oil supply shock from Baumeister and Hamilton (2019).

We interact the shock with Z_{ij} which represents i, j or ij specific (time-invariant) characteristics (duration or relationship, importance of i in j, market share of i or j, etc). We also consider a set of controls X_{ij}.

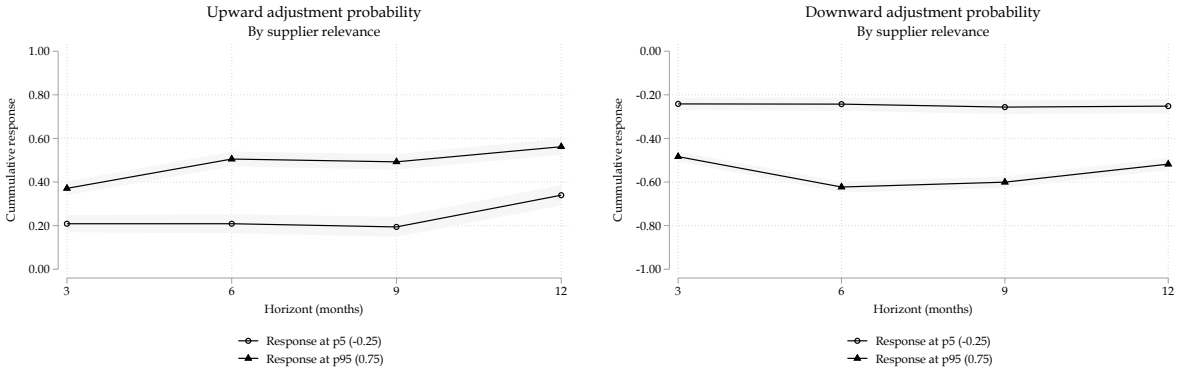
Figure 9 depicts the average probability of price adjustment after 3, 6, 9, and 12 months after the oil shock. We focus on suppliers in node J_1 and J_2 of Figure 1—this is, producers that use a large portion of oil in their production process. The left panel plots the response to oil price increases while the right panel shows the response to declines in oil prices. Prices are sticky. The average probability of increasing prices after a 1% increase in oil prices is 30% after three months and increases to 50% after 12 months. The probability of reducing prices is similar in the short run (3 months) but unlike the upward adjustment probability, the downward adjustment probability stays around 30% even after 12 months.

Figure 9: Probability of price adjustment to a 1% increase in oil prices



In Figure 10, we analyze the influence of supplier market shares (s_{ijs}) on price adjustments. Panel (a) reveals that suppliers with larger bilateral market shares (s_{ijs}) are more likely to increase their prices. Specifically, suppliers in the 95th percentile of the bilateral market share distribution have a three-month probability of raising prices that is twice as high—40% compared to 20%—as suppliers in the 5th percentile. This difference remains significant over a 12-month horizon, with dominant suppliers exhibiting a 60% probability of upward price adjustments, compared to a 40% probability for atomistic suppliers

Figure 10: Heterogeneity in the Extensive of Price Adjustment: Supplier Relevance



Panel b of Figure 10 shows a similar but less pronounced pattern for downward price adjustments in the face of oil price declines. Suppliers with higher market share have a higher probability of reducing prices.

6.2 The intensive margin adjustment

For the intensive margin of price adjustment we follow Jordà (2005) and estimate the following Local Projection-IV regression

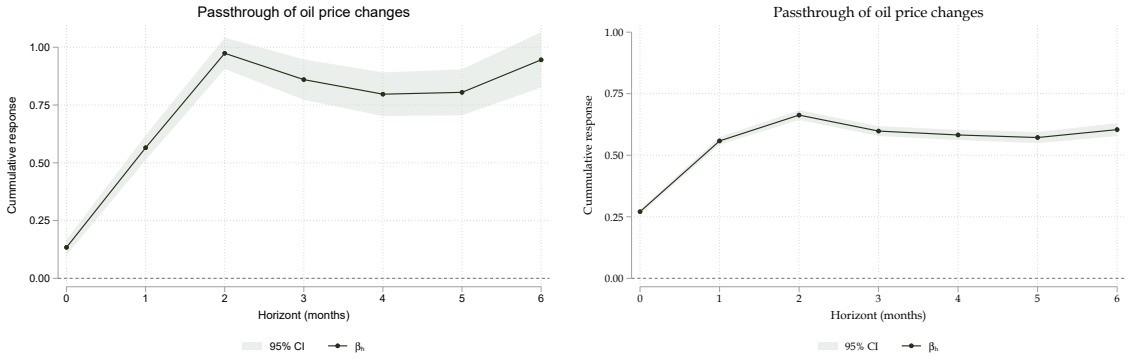
$$\pi^{K,ijv}_{t-1,t+h} = \alpha + \beta^K_h(\Delta \log \hat{P}^{oil}_{it}) + \phi^K_h(\Delta \log \hat{P}^{oil}_{it} \cdot Z_{ijt}) \tag{4}$$

$$+ \sum_{j=1}^{12} \delta^j \pi_{t-j} + \sum_{j=1}^{12} \gamma^j \Delta P_{c,t-j} + \psi X_t + \varepsilon_t, \tag{5}$$

where $\pi^{ijv}_{t-1,t+h}$ is the log change of prices from period $t+h$ compared to period $t-1$ for supplier i, selling product v to customer j.

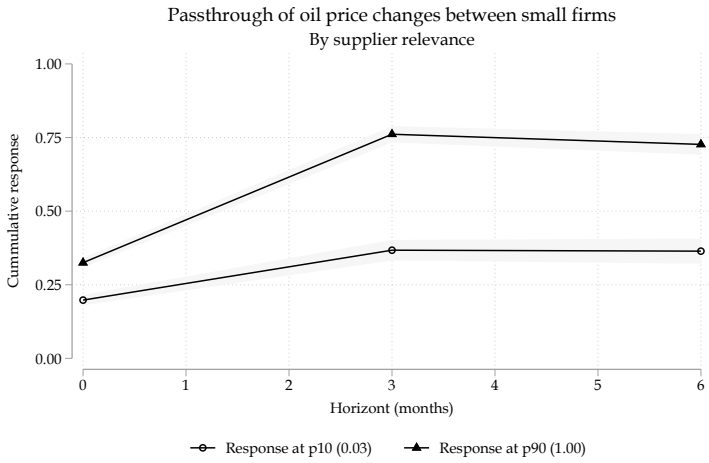
In Figure 11 we plot the response of prices at different nodes in the network. The left panel shows evidence of full pass-through after two months for the main oil suppliers in the chilean economy (node J_0 in Figure 1). The right panel shows the pass-through of the main clients of oil suppliers (importers) in Chile (nodes J_1 and J_2 in Figure 1). The initial pass-through is 0.25 and then reaches a value slightly above 0.5, meaning that a one percent increase in oil prices generates, after 6 months, a 0.5% increase in the price of goods sold by the key users of oil in the economy.

Figure 11: Price response of firms in oil extraction at initial node refinery industries



In Figure 12 we study the role of suppliers' bilateral market share. The on impact price pass-through is slightly larger for dominant suppliers (0.3 vs 0.24). However, after

Figure 12: Suppliers' bilateral market share and pass-through



six months, dominant suppliers' in the 90th percentile of the distribution of s_{ijs} present a pass-through of 0.75, which compares to a pass-through of 0.3 for firms in the 10th percentile of s_{ijs}.

7 Discussion on implications

Our facts provide evidence of the importance of bilateral market shares in driving the frequency of price change and, therefore, the pass-through of shocks. Existing models emphasizing market power and networks often assume flexible prices (Grassi et al., 2017; Alviarez et al., 2023; Dhyne, Kikkawa, and Magerman, 2022, e.g.,). The new generation of network models with sticky prices (e.g., Ghassibe, 2021) rely on monopolistically competitive firms with constant elasticity of demand, which rules out within industry market concentration as a driver of price settings. Mongey (2021) proposes a model with oligopolist firms and endogenous frequency price change as a function of market power. However, such a model abstracts from market power within firm-to-firm relationships. Our facts point to incorporating state-dependent price rigidity in menu cost models of networks and non-constant demand elasticity.

7.1 A model of state-dependent pricing in firm-to-firm relationships

Our goal is to extend the models in Gopinath and Itskhoki (2010) and Klenow and Willis (2016) to firm-to-firm relationships. In a simple setup, a monopolist supplier faces menu costs, information rigidities, and non-constant demand elasticity (variable markup) as in Gopinath and Itskhoki (2010). The probability of price adjustment is a function of the effective elasticity of demand and the super-elasticity of demand (the change in the elasticity when prices change). In this context, the frequency of price adjustment, and the pass-through, decrease with the super-elasticity of demand, which in turn is decreasing in the effective market share of the supplier. Suppliers with larger market share can increase prices without sacrificing much profits.

7.2 Role of heterogeneity: time-dependent pricing

A direct and simpler implication of our facts is that sectoral price heterogeneity emphasized by Rubbo (2023) and Pasten, Schoenle, and Weber (2020) still masks significant heterogeneity across sectors. Indeed, Figure 19 of our Appendix shows that all the firm-to-firm heterogeneity also manifests in sector-to-sector heterogeneity. This additional degree of heterogeneity in price rigidity can generate non-linear propagation and have relevant macroeconomic implications.

8 Conclusion

Our findings emphasize the critical role of firm-to-firm relationships in shaping price adjustment behavior, highlighting the importance of match-specific characteristics in driving the heterogeneity of price adjustment decisions. Specifically, we show that suppliers' market share in their clients' purchases is a key determinant of the likelihood of price adjustments in response to external shocks, such as oil price fluctuations. The asymmetric pass-through of positive versus negative shocks further emphasizes the influence of

bilateral market power on price-setting dynamics. These results suggest that traditional models of state-dependent pricing, which incorporate menu costs and variable demand elasticities, should consider the role of market power within supplier-client networks. The implications for understanding inflation dynamics and the transmission of monetary policy can be significant, particularly given the pronounced heterogeneity in firm-to-firm relationships compared to sectoral-level differences. This is especially relevant during periods of substantial shocks, such as the COVID-19 pandemic, where the granular nature of these relationships seems to play a more critical role in shaping economic outcomes.

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Appendix

Table 6: Extensive Margin Variance Decomposition: Subclass level

Table 7: Extensive Margin Variance Decomposition

Figure 13: Size and subclasses

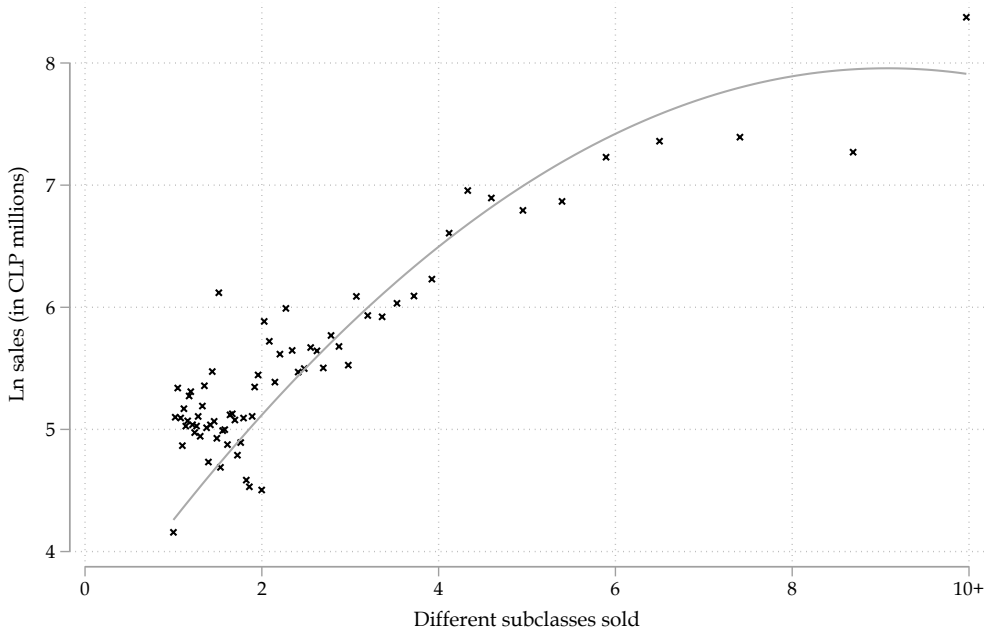
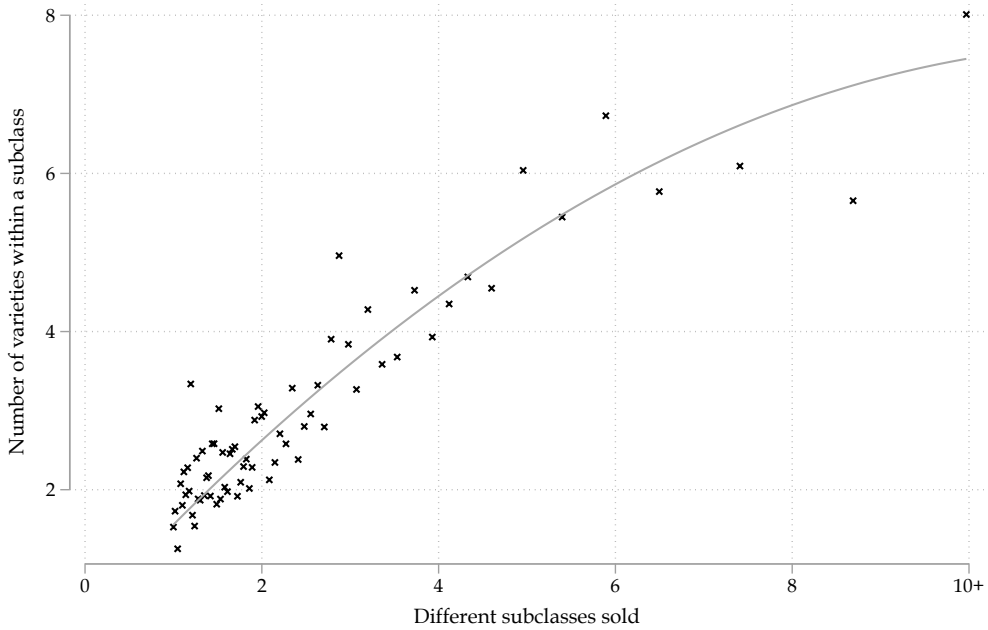


Figure 14: Variety and subclasses



8.1 Competitors price gap

Here we study the extent of strategic complementarities in our data. Figure 15 shows the distribution of competitors' price gap, as defined in Karadi, Schoenle, and Wursten (2024). For each firm, we measure the average price of the competitors within the product subclass market. As seen in Figure 15, we observe that the price gap is centered around zero, with most of the prices below or above 50% the average price of the market.

In Figures 16 and 17 we confirm the results in Karadi, Schoenle, and Wursten (2024). The magnitude of the price change increases with the distance from the average price of the competition. Also, firms are more likely to change the price when they deviate from the competitor's price.

As Karadi, Schoenle, and Wursten (2024) emphasize, these facts are consistent with state-dependent price-setting models in which menu costs are random (e.g., Dotsey, King, and Wolman, 1999; Luo and Villar, 2021; Alvarez, Lippi, and Oskolkov, 2022).

Figure 15: Competitor-price gap (strategic complementarities)

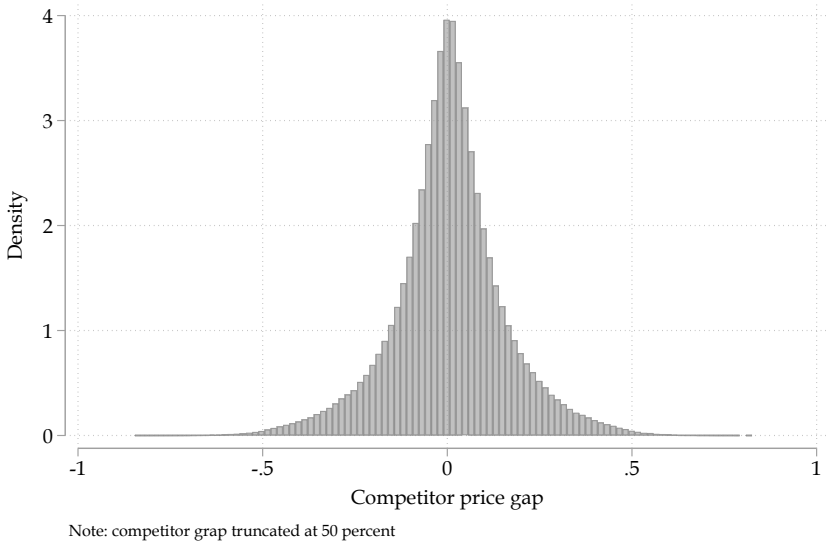
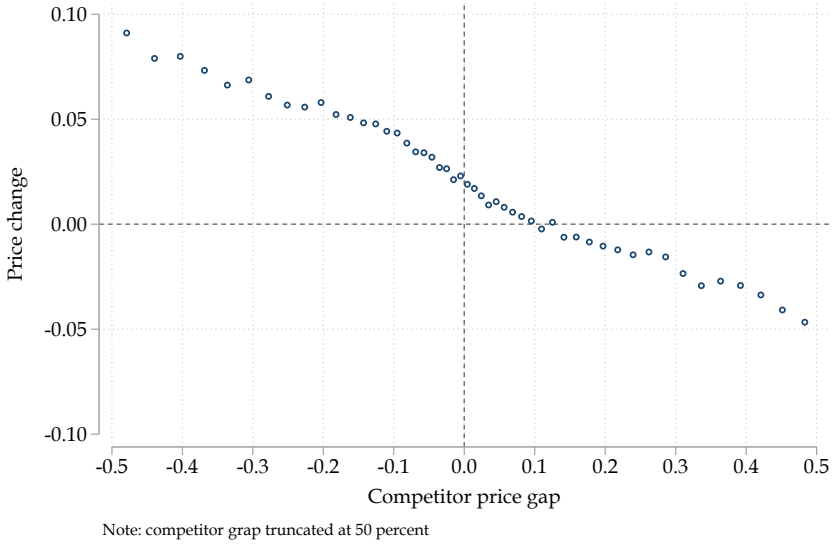


Figure 16: Magnitude of adjustment (t+1) as function of the gap

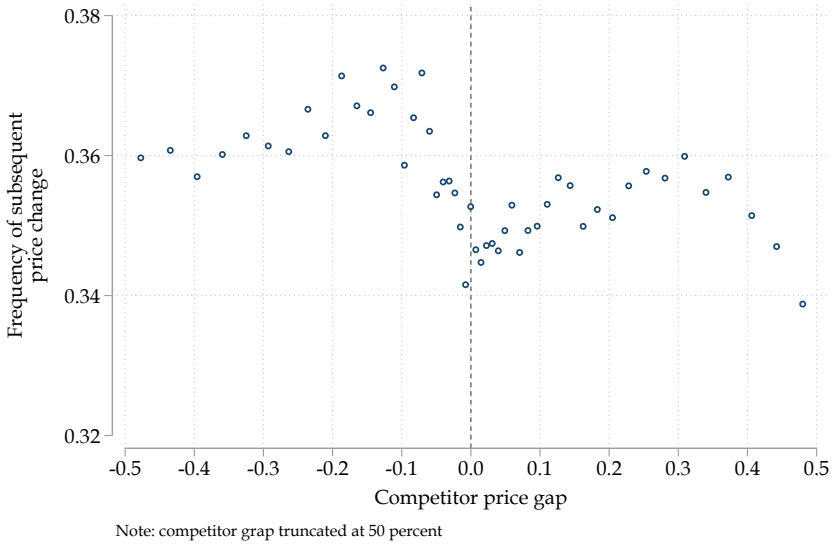


Version: Filtered of supplier-product FE using OLS

8.2 Sectoral heterogeneity

We now explore the heterogeneity in sectoral frequency price change within the PPI sample. Figure 18 reports the median and the weighted average frequency price change for the 111 sectors in our sample. Two facts stand out. First, as documented by Pas-

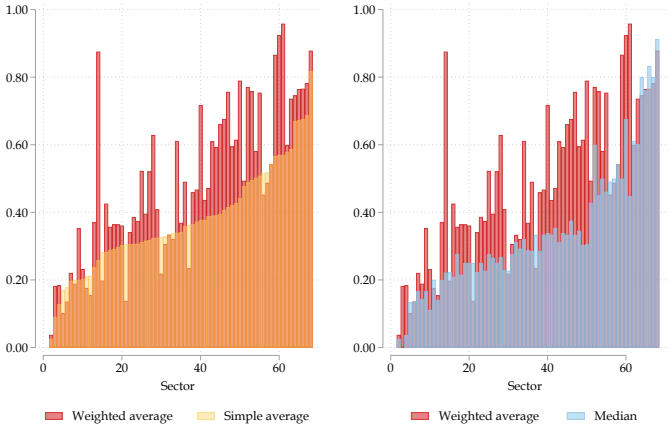
Figure 17: Magnitude of adjustment as function of the gap



Version: Filtered of supplier-product FE using OLS

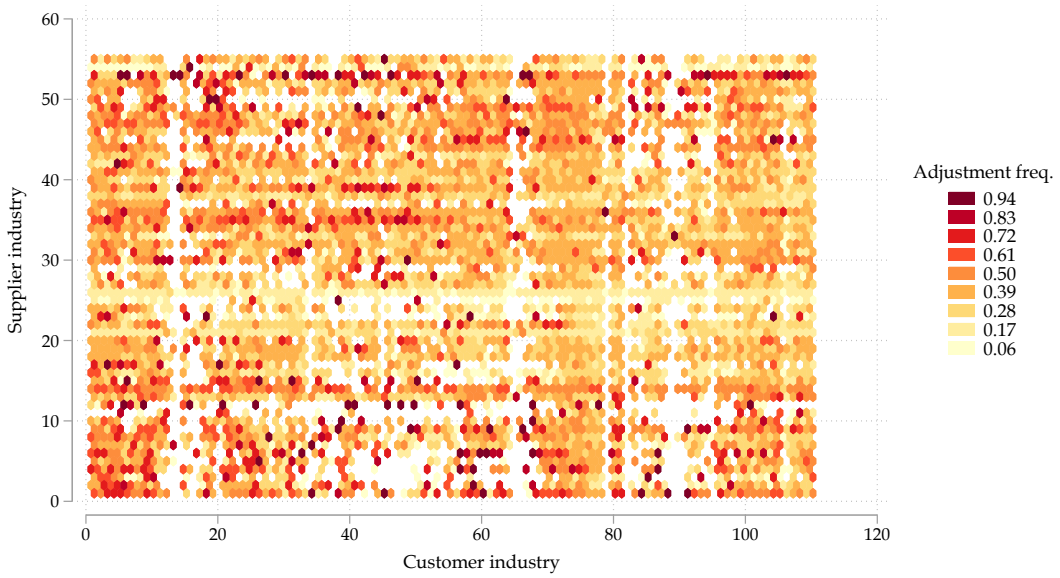
ten, Schoenle, and Weber (2020), there is large sectoral heterogeneity in frequency price changes. Second, there is still significant heterogeneity within sectors, as expressed by the difference between the median and the weighted average frequency of price change. Most sectors display a weighted average that is significantly larger than the median. For example, in many sectors, the weighted average is up to 3-4 times larger, indicating that large firms tend to change prices more frequently within sectors.

Figure 18: Frequency of adjustment between sectors (CAE 111 industries)



We now document an additional degree of heterogeneity in sectoral frequency price changes. We calculate the frequency price change at the i supplier-client level. Figure 19 plots the sector-to-sector frequency price change. The vertical axis represents the supplying sector and the horizontal axis represents the customer sector. Light colors indicate low-frequency price change and darker colors represent high-frequency price change. We observe significant heterogeneity in frequency price changes from a given supplier sector to different customer sectors.

Figure 19: Sector-to-sectort frequency of adjustment between sectors (CAE 111 industries)



f_{IJ}: monthly frequency of price IJ changes ($> 0.5\%$) for all IJ transactions (average across goods and time: 2018.m1-2023.m6)