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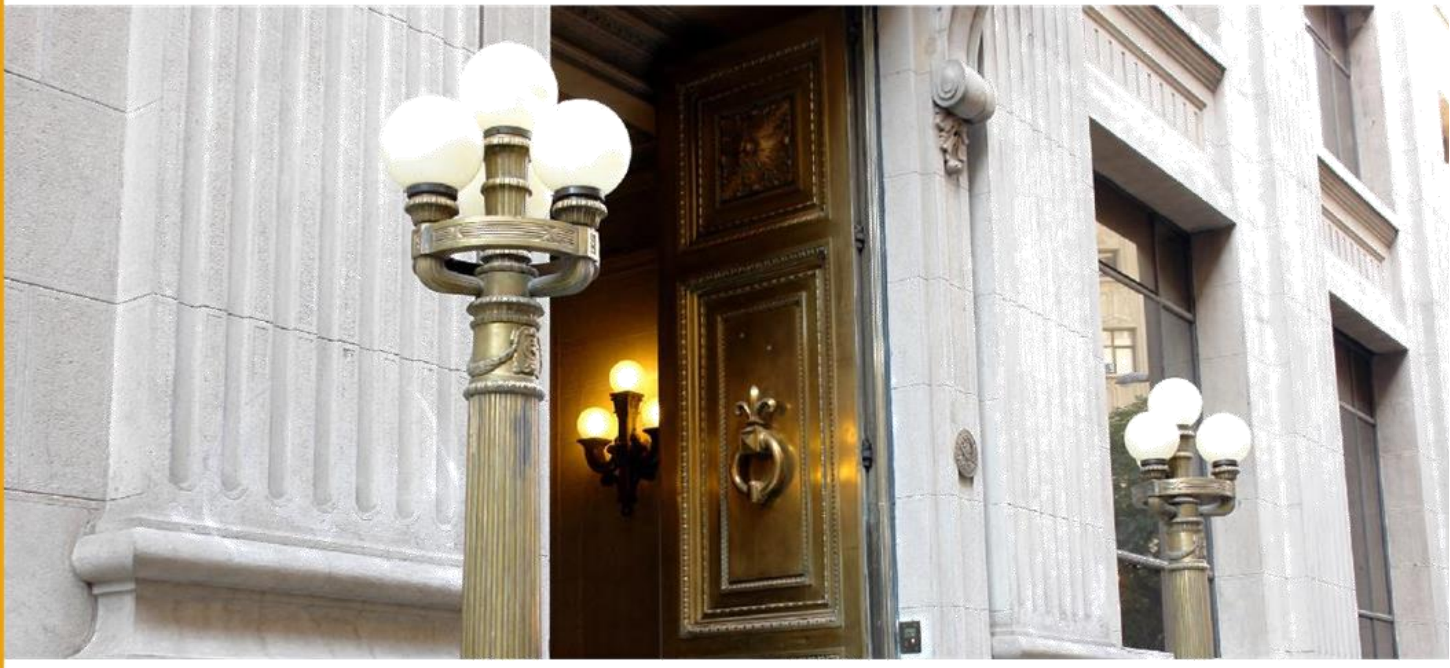

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Abstract

We leverage a comprehensive dataset of electronic invoices from Chilean firms to document new facts on price dispersion across buyers of the same manufactured intermediate goods. Over half of firm-to-firm sales in manufacturing are accounted for by products that are purchased by more than one buyer in a given month, with prices ranging by 40 percentage points across buyers for the average product. Price dispersion is pervasive across all manufacturing sectors. Observable characteristics of products and of buyer-seller pairs (including distance, mode of payment, and size of the parties and of the transaction) explain only a small fraction of the variance of price gaps in the data. We use a workhorse model of production networks to quantify the productivity gains from eliminating markup dispersion across buyers of individual products, inferring initial differences in markups from observed price gaps. The increase in aggregate productivity relative to the sales share of treated multi-buyer firms ranges from 2 to 7 percent, depending on the calibration of elasticities of substitution. The gains from eliminating markup dispersion across buyers are as large as those of eliminating markup dispersion across products.

Resumen

Utilizando datos de factura electrónica de firmas chilenas, documentamos nuevos hechos estilizados sobre dispersión de precios entre compradores de un mismo bien intermedio manufacturado. Más de la mitad de las ventas entre firmas desde el sector manufactura proviene de productos que poseen más de un comprador en un mes, con precios que varían, para el producto promedio, en 40 puntos porcentuales entre sus compradores. La dispersión de precios es generalizada en todos los sectores de manufactura. Características observables de los productos y de la relación vendedor-comprador (como distancia, modo de pago, tamaño de las partes y de la transacción) explican sólo una pequeña fracción de la varianza de la diferencia de precios en los datos. Usamos un modelo macro de producción en redes estándar para cuantificar las ganancias en productividad de eliminar la dispersión de markups entre compradores de un mismo producto, donde las diferencias iniciales en markups provienen de la diferencias de precios observadas. El aumento en productividad agregada relativa a la participación en ventas de firmas con más de un comprador varía entre 2 y 7 por ciento, dependiendo de la calibración de la elasticidad de sustitución. Las ganancias de eliminar la dispersión de markups entre compradores de un mismo producto son de magnitud similar a las de eliminar la dispersión de markups entre productos.

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1 Introduction

To what extent do different firms pay disparate prices for the same intermediate input? Which observable characteristics of buyers and sellers account for the variation in prices across buyers? Is dispersion in input prices across buyers an important source of misallocation in domestic production networks? Answering these questions is important for guiding models of firm-to-firm trade and for understanding inefficiencies in domestic supply chains. However, existing evidence on price dispersion for intermediate inputs is scarce, and limited to detailed products within specific industries or to international trade transactions.[1]

This paper uses comprehensive firm-to-firm data from Chile to document new facts on price dispersion across buyers of intermediate inputs and to quantify the extent of misallocation resulting from this price dispersion. Our analysis is based on transaction-level price data extracted from electronic invoices issued by Chilean firms. Crucially, these invoices include detailed product codes and descriptions that we use to uniquely identify manufacturing products. They also contain information on the identities of the sellers and the buyers, which allow us to study how the price of a given product varies across buyers. The set of uniquely identified products represents almost half of Chilean manufacturing sales, and the industry composition and the changes in prices in our data closely track the Chilean Producer Price Index.

We start by showing that manufacturing products are frequently sold to multiple firms, and that these firms regularly pay different prices for the same product. More than half of firm-to-firm sales are accounted for by products that are purchased by more than one buyer in the same month. For the average product with multiple buyers, the range in log prices across buyers is 0.34 (40 percentage points) and the cross-buyer standard deviation in log prices is 0.07. We show that the observed dispersion in prices is pervasive across disparate manufacturing sectors, ranging from Food, to Chemicals, to Electrical Equipment. Price dispersion is more pronounced for products that are sold by larger sellers, have higher sales volume, and are purchased by a larger number of buyers.

We then evaluate how observed 'price gaps', i.e. the difference between the price that a buyer pays and the product's average price across buyers, are related to observable characteristics of the buyers, sellers, and products. Price gaps are highly persistent over time, correlated across different products purchased by the same buyer, and across products within buyer-seller pairs. We also show that prices are lower for larger buyers and

[1] See e.g. Grennan (2013), Marshall (2020), Fontaine et al. (2020) and Alviarez et al. (2023). We discuss this literature below.

for buyer-seller pairs with older relations and higher volume of sales, and are negatively correlated with transacted quantities. We also find evidence of quantity discounts. All of these observable characteristics, however, account for a very small fraction of the variance of price gaps in the data. Whereas sellers charge different prices across buyers, we do not find strong evidence that buyers face fixed price-quantity menus (instead, quantities do not move one-to-one with prices). Finally, we show that the distance between the buyer and seller and the form of payment by the buyer (cash or credit) play a minimal role in accounting for the observed price gaps. These two observations suggest that price gaps reflect differences in markups rather than differences in the marginal costs of supplying different buyers.

Motivated by these facts, we use a workhorse model of a production network to quantify the welfare costs of markup dispersion across buyers. The model is populated by a discrete number of firms that produce differentiated products using intermediate inputs and an inelastically supplied factor. Firms can potentially produce multiple products, which are sold to other firms or to final consumers. Since price gaps are not easily accounted for by observable characteristics of the products and buyers, we introduce markups as exogenous wedges that vary at the product-buyer level. Motivated by our evidence, we assume that buyers can choose quantity at a given price. As in Hsieh and Klenow (2009) and Baqaee and Farhi (2020), dispersion in wedges can distort the allocation of inputs across buyers and reduce allocative efficiency.

We use the model to evaluate changes in aggregate welfare from eliminating markup dispersion across buyers of the same product, while keeping average product-markups unchanged. Under the assumption that the marginal cost of each product does not vary with the identity of the buyer, differences in initial markups across buyers can be measured from observed price gaps. We can thus conduct this counterfactual without estimating markup levels for each product-buyer pair, which requires much stronger assumptions (see e.g. Loecker et al. 2016 and Dhyne et al. 2022a). Since we do not observe product-level prices for non-manufacturing products nor for final sales, we keep markups for these products unchanged.

In addition to the change in wedges, this counterfactual requires parameterizing the full network of input uses and assigning values to the share of intermediate inputs in production for each firm, and the share of each firm in total sales. Rather than making distributional assumptions, we target them directly by mapping each product in the model to a product in the Chilean data. We assign values of elasticities of substitution across products and inputs from the literature.

Eliminating markup dispersion across buyers increases aggregate welfare by 0.2% in the low elasticity of substitution calibration. Since we do not observe markup variation for final sales and for non-manufacturing firms, this counterfactual applies to firms that represent only 8% of total sales. The change in welfare normalized by the fraction of sales of treated firms is 2.2%. In the high elasticity of substitution calibration, the normalized change in welfare is 7.3%.

To put these gains in perspective, we compare them with a second counterfactual in which we eliminate markup dispersion across buyers and products. Specifically, we set markups for all manufacturing intermediate sales to the economy-wide ratio of revenues to costs. To implement this exercise, we must assign values to the average initial markup of each product, which we do under stronger assumptions as the ratio of revenues to costs of the producer. Eliminating markup dispersion across buyers and products results in welfare gains that are slightly more than double the gains from eliminating markup dispersion across buyers alone. In other words, markup dispersion across buyers is almost as costly as markup dispersion across products.

Related literature. Most of the evidence on price dispersion is based on consumer prices. For example, Kaplan and Menzio (2015) and Kaplan et al. (2019) measure the extent of consumer price dispersion within and across retail stores, while DellaVigna and Gentzkow (2019) and Daruich and Kozlowski (2023) document the practice of uniform prices within large retail chains. Evidence of cross-buyer price dispersion for intermediate inputs is largely limited to specific industries. For example, Grennan (2013) studies price dispersion across buyers of medical devices, while Marshall (2020) focuses on wholesale prices paid by different New York restaurants for the same good on the same day. Other papers examine dispersion in unit values in trade data. Fontaine et al. (2020) use French customs data to document differences in unit values across buyers within CN8 product categories sold by the same exporter. This variation may in part be attributed to product heterogeneity within CN8 categories, as noted by Fontaine et al. (2020).[2] Relatedly, Alviarez et al. (2023) show that unit values differ across US importers purchasing the same HS10 product categories from the same foreign supplier. Our contribution is to provide comprehensive evidence of price dispersion across buyers in the firm-to-firm domestic network for detailed manufactured goods.

Our paper is also related to an extensive literature studying misallocation due to

[2] CN8 ("Combined Nomenclature 8-digits") categories are used to classify imports and exports in the EU to determine customs duties. Examples of CN8 categories for top French exports reported by Fontaine et al. (2020) are: "Aeroplanes and other powered aircraft of an unladen weight >15,000 kg", "Motor cars and other motor vehicles principally designed for the transport of persons", and "Champagne of actual alcoholic strength $\geq 8,5\%$ vol."

markup dispersion (see e.g. Peters 2020, Baqaee and Farhi 2020, Edmond et al. 2023, Pellegrino 2023, Osotimehin and Popov 2023). Whereas some of the models considered are flexible enough to allow for a buyer-seller specific definition of products, a standard assumption when mapping these models to data is that firms charge common markups across all buyers.[3] Closer to us is Dhyne et al. (2022b), who study the gains from eliminating markup dispersion across buyers of the same product, inferring buyer specific markups using a model of endogenous markups and market share data. In contrast, we infer differences in markups across buyers using data on product-buyer specific prices, under the assumption that marginal cost of production are common to all buyers of the same product. Bornstein and Peter (2023) study the cost of markup dispersion across firms and buyers in a model in which sellers set non-linear prices. Our quantitative model assumes that sellers are able to price discriminate across buyers but, motivated by our evidence, each buyer faces linear prices when choosing input quantities.

The reminder of the paper is organized as follows. Section 2 introduces the data. Section 3 reports our empirical findings. Section 4 presents our quantitative framework and analytical results. Section 5 presents the results of our counterfactual exercises, and the last section concludes.

2 Data

In this section we introduce the dataset we use to calculate measures of price dispersion and present basic summary statistics.

2.1 Data description

Our analysis is based on price and quantity data from domestic transactions among Chilean firms. Starting in 2017, the Chilean Internal Tax Service mandated the use of electronic invoices for all firm-to-firm sales. Our dataset encompasses all invoices dated from January 2019 to December 2022, and was obtained through the Central Bank of Chile.[4]

[3]The welfare cost of inflation in sticky price models depends crucially on how inflation impacts the dispersion of relative prices across goods. Nakamura et al. (2018) and Alvarez et al. (2019) use the micro data underlying the consumer price index to measure the link between inflation and the distribution of price changes. We document very small changes in the dispersion of markups across buyers in Chile as the inflation rose by more than 10 percent between 2022 and 2023.

[4]This paper was developed within the scope of the research agenda conducted by the Central Bank of Chile (CBC) in economic and financial affairs of its competence. The CBC has access to anonymized information from various public and private entities, by virtue of collaboration agreements signed with these institutions. 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 individuals

The invoices comprise two main sections: the "Heading" and the "Detail". The Heading section includes essential information regarding the invoice, such as the date, tax identifiers for both the seller and the buyer, the municipalities where they are located, and the payment terms (cash or credit). The Detail section contains specific information about the products sold. Each product is represented by an individual entry within this section. Entries include a description (e.g. "Maule Graphics GC1 315GR 77X110 2500 PL") and a product code (e.g. "ED003C3V59025A") which identify the items being traded.[5] Additionally, the entries include price, quantity, and any applicable discounts or surcharges for each product.[6]

In what follows, we use the terms "firm" to refer to a unique tax ID, and "establishment" to refer to a tax ID-municipality duplet. The Central Bank of Chile assigns each firm to a 3-digit ISIC Rev. 4 sector. We treat all establishments of the same firm as a single seller or buyer.

We identify unique products utilizing the items' descriptions and codes. These codes can take different forms, such as EAN (European Article Number) codes or internal codes used by the seller, and are only available to us starting in June 2021.[7] We focus on non-oil manufacturing products that are assigned codes consisting of at least three characters. In our baseline analysis, we define a unique product as a triplet comprising the product description, the product code, and the establishment from where it is sold. Thus, identical product codes issued by the same seller from different establishments are considered distinct products. For each seller, we discard codes associated with multiple descriptions, as well as descriptions that are associated with multiple codes. We conduct robustness exercises using the smaller sample of products for which EAN product codes are available.

We take the following additional steps to clean the raw data. First, we address potential typos in the invoices by removing transactions that exceed 100 billion pesos (approximately 125 million USD) or that have non-positive recorded prices or quantities. Second, we discard invoices in which the tax ID of the seller matches that of the buyer. Third, we

or firms. Officials of the CBC processed the disaggragated data. All the analysis was implemented by the authors and did not involve nor compromise SII. The information contained in the databases of the SII is of a tax nature originating in self-declarations of taxpayers presented to the Service; therefore, the veracity of the data is not the responsibility of the Service.

[5]This particular product is a fully coated folding white boxboard used for the production of medical and healthcare packaging.

[6]For an invoice to be valid, the Chilean Internal Tax Service only requires the seller's and buyer's tax ID's, the text description of goods sold, the total amount paid, and a date. More information can be found (in Spanish) at https://www.sii.cl/factura_electronica/formato_dte.pdf.

[7]The Central Bank of Chile has a data agreement with Chilean Internal Tax Service, which incorporates several tax forms and documents. Not all the data in the Chilean Internal Tax Service is part of this agreement.

eliminate invoices that were later cancelled or deemed invalid. Fourth, we merge the invoices with the firm's wage and tax statements and discard firms that do not declare any paid workers. Finally, to be conservative in our estimates of price dispersion, we eliminate transactions where the product's recorded price deviates from the average price recorded in other transactions from the same month by more than 1 log points. Appendix B describes these datasets and cleaning steps in detail.

2.2 Summary statistics

We are interested in analyzing dispersion in prices across buyers who purchase the same product within a narrow period of time. Most of our baseline analysis focuses on transactions occurring during June 2021, the first month in which product codes are available in the data. We focus on this month as it was proceeded by a year of relatively low PPI inflation in Chile.[8] Table 1 reports summary statistics for the sample of invoices issued by manufacturing firms in June 2021. These statistics do not vary much across months between June 2021 and June 2022.

The first column provides an overview of the entire sample, revealing a total of 5 million invoices amounting to 5.1 billion USD in sales. The second column focuses on the sample of products that can be uniquely identified. This sample covers 2.3 million invoices and 9.6 million transactions, representing almost half of total manufacturing sales (2.4 USD billion). Even though the fraction of sellers using product codes is relatively small (4,787 out of 49,280), they account for a disproportionally large fraction of sales and invoices. Within this sample, we were able to identify 439,205 unique products and 159,124 buyers. Products that where purchased by more than one buyer account for 53% of sales in this samples.[9] In June 2021, the average product was sold to 8.3 buyers and each buyer purchased the same product 2.6 times. For products with multiple buyers, the average number of buyers is 20.3 and the median is 4.

The third column of Table 1 reports summary statistics for the sample of products that have EAN codes. These products constitute a small portion of the total sales (0.4 billion USD) and are used by only 275 sellers. Products with EAN codes are more frequently sold to multiple buyers and have a higher average number of buyers.

[8] Manufacturing PPI inflation was 0.2% between 06/19- 06/20, 11% between 06/20- 06/21, and 25% between 06/21- 06/22.

[9] For the June 2021-June 2022 period, the fraction of sales accounted for by multi-buyer products is 67%.

Table 1: Summary statistics

	All	Baseline	EAN codes
Sales (USD bill.)	5.1	2.4	0.4
Invoices (mill.)	5.0	2.3	0.6
Transactions (mill.)	21.8	9.6	3.0
Sellers	49,280	4,787	275
Buyers	401,930	159,124	58,914
Products		439,205	55,187
Buyer-seller pairs		444,372	76,704
Buyer-product pairs		3,651,790	752,726
Buyers per-product		8.3	13.6
Transactions per buyer-product		2.6	4.0
Products with more than one buyer:			
Share of sales		0.53	0.68
Buyers per-product		20.3	25.4
Buyers for median product		4.0	4.0
Transactions per buyer-product		5.9	9.8
Transactions for median buyer-product pair		2.0	3.0

Notes: The table reports summary statistics for different sample of invoices. 'All' refers to all manufacturing invoices in June 2021. 'Baseline' refers to our baseline sample, which identifies unique products and also cleans the data as described in the text. 'EAN codes' refers to the sample of invoices where products can be identified using EAN codes.

Comparison to official price statistics. Table 2 shows the industrial composition and the inflation rate by sector in our baseline sample and in the official Producer Price Index (PPI) data. The largest sector in our sample is 'Food', followed by 'Chemicals'. Importantly, the sectorial shares in our data are very similar to those in the PPI: the correlation is 0.96. The level and cross-sectoral variation in inflation rates are also very correlated in our data and in the PPI data.

Table 2: Comparison with official PPI data

	Share of sales		Inflation 06/21-06/22	
	Sample	PPI	Sample	PPI
Food	43.8	34.3	34.1	25.5
Beverages	5.9	10.3	15.0	9.8
Textiles	0.8	0.0	15.4	NA
Wood products	4.9	5.0	24.8	22.0
Paper	4.8	8.7	37.7	25.3
Printing	0.2	1.7	15.2	23.3
Chemicals	13.0	11.2	46.4	46.5
Pharmaceutical	4.8	3.1	8.1	6.3
Plastic, rubber	5.4	4.3	22.3	19.6
Non-metallic minerals	5.4	4.8	25.9	28.1
Metals	4.6	2.6	18.0	16.9
Metal products	2.4	7.9	25.7	27.5
Electric equipment	1.0	0.6	19.5	6.6
Machinery and equip	0.9	3.6	22.2	12.5
Furniture	1.7	1.9	14.6	11.9
Other	0.4	0.0	12.3	NA
Correlation	0.96		0.84	

Notes: The first panel reports the share of each manufacturing sub-sector in total 'non-oil' manufacturing sales. The first column reports the shares for the baseline sample, and the second column reports the shares used by the Chilean Institute of National Statistics for the computation of the Producer Price Index (PPI). The second panel reports the inflation between June 2021 and June 2022 for each sub-sector. The third column reports inflation in our sample, computed as a weighted average of log-price changes with weights based on sales shares in the invoices. The fourth column reports the official PPI inflation in each sector.

3 Empirical findings

In this section we present our central empirical findings. We first analyze dispersion in prices across buyers that purchase the same product within a particular month, and analyze how it varies across products, sellers, and sectors. We then show that the observed price gaps are not driven by transportation costs or by staggered changes in prices across buyers. Next, we investigate how price gaps vary by characteristics of the buyer and the buyer-seller relation. Finally, we evaluate the importance of quantity discounts and explore whether our measure of price gaps is consistent with the presence of price/quantity menus.

3.1 Price dispersion across buyers

Let $p_{ib\tau}$ denote the price (after discounts and surcharges) of product i purchased by buyer b in transaction τ. Denote the price gap for transaction τ by

$$\mu_{ib\tau} \equiv \log\left(p_{ib\tau}/p_i\right), \tag{1}$$

which represents the deviation (in logs) of the transaction's price relative to some average p_i of prices paid for product i. Our results in this section do not depend on the value of p_i.

We start by showing that for a given product, within a month, most of the dispersion in price gaps is across buyers rather than across transaction of the same buyer. To do so, we fit regressions of $\mu_{ib\tau}$ on a full-set of product-buyer fixed effects for the sample of products purchased by multiple buyers during June 2021. Table 3 reports the Partial R-squared of these regressions relative to a reduced model that only includes product-level fixed effects.[10] The Partial R-squared is 0.73 if we assign the same weight to all transactions, 0.84 if we weight them according to sales, and 0.92 if we assign the same weight to each product and weight transactions of the same product by their share in the product's quantity.

Given that there is little variation in prices across transactions for a given product-buyer, we aggregate prices by product-buyer across transactions in each month "t" as $p_{ibt} \equiv \left[\sum_{\tau\in t} p_{ib\tau}q_{ib\tau}\right] / \left[\sum_{\tau\in t} q_{ib\tau}\right]$, and define the price gap for the ib pair as $\mu_{ibt} \equiv \log\left(p_{ibt}/p_{it}\right)$.[11] Unless noted otherwise, we focus on t =June 2021 and omit subscript "t" to streamline notation. We denote the vector of observed price gaps for different buyers of product i by $\boldsymbol{\mu_i}$.

[10]The partial R-squared equals $\left[1 - SSR^F/SSR^R\right]$, where SSR^F and SSR^R denote the sum of squared residuals of the full and the reduced model, respectively. This statistic gives the proportion of the variation explained by the full model that cannot be explained by the explanatory variables in the reduced model. Throughout this section, the reduced model used for the computations of the partial R-squared is a simple regression of price gaps and product fixed effects.

[11]Thus, $\mu_{ibt} = \left[\sum_{\tau\in t} \mu_{ib\tau}q_{ib\tau}\right] / \left[\sum_{\tau\in t} q_{ib\tau}\right]$, where $\mu_{ib\tau} = \log\left(p_{ib\tau}/p_{it}\right)$.

Table 3: Price dispersion within and across buyers

	(1)	(2)	(3)
Partial R2	0.73	0.84	0.92
Observations	8,389,573	8,389,573	8,389,573
Weights	None	Sales	Quantity

Notes: The Table reports the Partial R-squared of the model $\mu_{ib\tau} = FE_{ib} + \epsilon_{ib\tau}$ relative to the reduced model $\mu_{ib\tau} = FE_i + \epsilon_{ib\tau}$, where FE_i and FE_{ib} are a full set of product-level, and product-buyer level fixed effects. The regressions are estimated by OLS on the sample of products that where purchased by more than on buyer in June 2021. In Column 1, each transaction receives an equal weight. In column 2 transactions are weighted by their sales. In Column 3, each product receives an equal weight, and transactions of the same product are weighted according to the transaction's share in the product's quantity.

We calculate two measures of price dispersion for multi-buyer products. The first is the range of price gaps across buyers (in log differences), $r_i \equiv \max(\boldsymbol{\mu_i}) - \min(\boldsymbol{\mu_i})$. The second is the standard deviation of price gaps across buyers, $\sigma_i \equiv \text{stdev}(\boldsymbol{\mu_i})$.[12]

Table 4 presents the sales-weighted distributions of these two statistics across products. The first column reports the distribution of r_i, showing that the same product is frequently sold at very different prices across buyers during the same month. The range exceeds 0.49 for products accounting for 25% of sales. The median (average) range is 0.28 (0.34). For reference, the aggregate inflation for these products between June and July 2021 was only 0.02 in logs Hence, differences in prices across buyers within a month are much larger than differences in average product-level prices across months.

The second column presents the distribution of σ_i. For the average product, this standard deviation is 0.07, and it surpasses 0.1 for products accounting for 25% of sales. The average standard deviation is roughly half of that documented by Kaplan et al. (2019) for barcode-level consumer goods in the US. While they capture price differences for retail goods both within and across stores, our numbers are for intermediate goods sold from the same establishment.

Fontaine et al. (2020) also find large dispersion in unit values paid by foreign buyers of French products. They show that within CN8 product categories sold by the same exporter, the coefficient of variation of unit values across buyers averages 0.3.[13] As they note, this variation may in part be attributed to product heterogeneity within CN8 categories. In contrast, our analysis focuses on identical products. Despite this important difference, the price dispersion in our data is of the same order of magnitude to that

[12] The standard deviation is computed as $stdev(\boldsymbol{\mu_i}) = \sqrt{\sum_b \frac{q_{ib}}{\sum_b q_{ib}} \mu_{ib}^2 - \left[\sum_b \frac{q_{ib}}{\sum_b q_{ib}} \mu_{ib}\right]^2}$.

[13] If prices are log normally distributed, a coefficient of variation of 0.3 corresponds to a standard deviation of log prices of 0.29.

found in studies using retail and export price data.

Table 4: Input price dispersion across buyers

	r_i	σ_i
P1	0.00	0.00
P5	0.00	0.00
P10	0.03	0.01
P25	0.12	0.02
P50	0.28	0.06
P75	0.49	0.10
P90	0.74	0.16
P95	0.94	0.21
P99	1.27	0.35
Mean	0.34	0.07

Notes: r_i is the difference between the highest and lowest price gap for product i. σ_i is the sales-weighted standard deviation of price gaps across buyers of product i. The Table reports the distributions of r_i and σ_i, where the unit of observation is a product i, and products are weighted by their sales. The distributions only include products with multiple buyers. P1-P99 represent percentiles of the distribution.

3.1.1 Robustness

In Table 5 we reproduce column 2 of Table 4 (dispersion of price gaps) for different choices of samples and specifications. Column 'Unweighted' reports the unweighted distribution instead of the sales-weighted one. Column 'Transactions' is based on price gaps by transaction in June 2021 (rather than first aggregating prices by buyer). Notably, these distributions closely resemble the one in our baseline specification.

Column 'June 2022' repeats the baseline exercise using prices in $t =$ June 2022 rather than June 2021. Following June 2021, PPI inflation accelerated in Chile, from 11 percent between 06/20-06/21 to 25 percent between 06/21-06/22. We can observe that price dispersion remained relatively stable despite the higher inflation.

Column 'One year' uses product-buyer level prices calculated by aggregating prices across all transactions in the period from June 2021 to May 2022. The share of sales of products purchased by multiple buyers is larger (0.67 vs. 0.53) if we extend the period to a year, as different buyers purchase the same product in different months. However, Column 5 shows that, for products with multiple buyers, the dispersion of price gaps over the year is similar to that in June 2021.

Finally, Column 'EAN' reports results for the smaller sample of products identified by an EAN code. Recall from Table 1 that these products have a greater number of buyers and more dispersed prices across buyers. Relative to this EAN sample, our baseline sample provides a conservative estimate of the degree of dispersion.

Table 5: Within-product standard deviation of price gaps: Robustness

	Baseline	Unweighted	Transactions	June 2022	One year	EAN
P1	0.00	0.00	0.00	0.00	0.00	0.00
P5	0.00	0.00	0.00	0.00	0.00	0.01
P10	0.01	0.01	0.01	0.01	0.01	0.02
P25	0.02	0.04	0.03	0.03	0.03	0.04
P50	0.06	0.07	0.06	0.06	0.06	0.08
P75	0.10	0.12	0.11	0.10	0.09	0.13
P90	0.16	0.18	0.17	0.16	0.14	0.21
P95	0.21	0.23	0.22	0.21	0.19	0.28
P99	0.35	0.37	0.38	0.35	0.34	0.42
Mean	0.07	0.09	0.08	0.08	0.07	0.10

Notes: The table reports the distribution of the standard deviation of prices across buyers of the same product for different samples. The unit of observation in these distributions is a product i. Column 'Baseline' uses our baseline sample, the distribution and standard deviation are weighted by sales, and the prices are aggregated at the buyer level and include all June 2021 transactions; $p_{ib} = [\sum_\tau p_{ib\tau}q_{ib\tau} / \sum_\tau q_{ib\tau}]$ for $\tau \in$ June 2021, as in Table 4. Column 'Unweighted' uses unweighted standard deviations. Column 'Transactions' uses transaction level price gaps $\mu_{ib\tau}$ instead of aggregating at the buyer level. Column 'June 2022' aggregates prices at the buyer level using all transactions in June 2022. Column 'EAN' uses the sample of products that can be identified by an EAN code. The distributions only include products with multiple buyers. P1-P99 represent percentiles of the distribution.

3.1.2 Which products have more dispersed prices?

We now study how the degree of price dispersion relates to product characteristics. We start by examining variation across manufacturing subsectors and across the seller size distribution. Appendix Table A.1 reports the distributions of σ_i for each manufacturing subsector, showing that price dispersion is pervasive across all subsectors. The sectors with the most dispersed prices across buyers are 'Pharmaceuticals' and 'Paper' (average σ_i of 0.1), while the sectors with least dispersed prices are 'Beverages' and 'Wood products' (average σ_i of 0.05). Appendix Table A.2 groups sellers into employment size quartiles and reports distributions of σ_i by quartile. Conditioning on products with multiple buyers, small sellers tend to have more uniform prices (average σ_i is 0.06) than large sellers (average σ_i is 0.08).

To further examine the relation between price dispersion and size, we fit regressions of the form

$$\sigma_i = \beta' \mathbf{X}_i + FE_j + \epsilon_i. \tag{2}$$

The unit of observation is a product and the dependent variable is the standard deviation of price gaps across buyers of the product and $\mathbf{X}_i$ contains different measures of the size of the product. All regressions include sector fixed effects and focus on the sample of products that are purchased by more than one buyer.

Column 1 of Table 6 shows a positive relation between seller size (measured using employment) and price dispersion across buyers. Column 2 shows a positive relation between product sales and price dispersion, and Column 3 shows a positive relation between number of buyers and price dispersion.

Finally, Column 4 reports partial elasticities from a regression that introduces all these variables simultaneously. While the estimated elasticities are statistically different from zero, the R-squared is lower than 10%, indicating that these characteristics account for a small fraction of the variation in dispersion across products in our sample.

Table 6: Price dispersion and product type

	(1)	(2)	(3)	(4)
log $\text{emp}_{s(i)}$	0.0064***			0.0036***
	(0.0002)			(0.0003)
log $\text{sales}_{s(i)}$		0.0067***		0.0037***
		(0.0002)		(0.0002)
log $\text{\#buyers}_{s(i)}$			0.0152***	0.0099***
			(0.0003)	(0.0004)
R^2	0.0501	0.0741	0.0725	0.0906
Observations	166,094	166,094	166,094	166,094

Notes: The table reports the results of estimating equation (2) by OLS. All columns include sector fixed effects. $\text{emp}_{s(i)}$ refers to the number of employees working for the seller of product i. $\text{sales}_{s(i)}$ and $\text{\#buyers}_{s(i)}$ respectively denote the value of sales and the number of buyers of product i in June 2021. Standard errors in parentheses are clustered at the seller level . * significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

3.2 Price gaps and differences in costs of supplying different buyers

The distance between the buyer and seller and the form of payment by the buyer (cash or credit) can induce differences in the cost of supplying different buyers. In this section we show that these two observable characteristics play a small role in accounting for the observed price gaps in our data.

3.2.1 Shipping costs

Does the observed dispersion of prices across buyers reflect differences in the cost of shipping products to buyers in different locations? To examine this question, we use information on the seller's and buyer's municipality reported in the invoices. We compute the distance between the selling establishment and each buyer as kilometers between the capital cities of their respective municipalities.[14]

We start by fitting the following regression of price gaps on distance:

$$\mu_{ib} = \mathbb{I}\left(\log \text{dist}_{ib} = 0\right) + b_1 \log \text{dist}_{ib} + FE_i + \epsilon_{ib}. \tag{3}$$

Here, $\text{dist}_{s(i)b}$ is the distance between the establishment that sells product i and the buyer, $\mathbb{I}\left(\cdot\right)$ is an indicator for whether the selling establishment and buyer are in the same municipality, and FE_i is a product fixed effect.

Column 1 in Table 7 shows that the coefficient on the indicator variable is negative: price-gaps are on average 0.008 lower when the seller and the buyer are in the same municipality. The coefficient on distance in Column 2 is positive, indicating that the price tends is increasing in distance between seller and buyer. Column 3 reveals that this relation is non-linear.

While the coefficients on distance are statistically different from zero, their economic significance is small. For the average product, the log difference in distance between the closest and the farthest buyer is 1.3 (3.7 km), which according to the estimates in Column 3 implies a log difference in the prices for these two buyers of only 0.009 if we assume that the closest buyer is in the same municipality as the seller. The largest log distance between two establishments in our sample is 8.4 (4,624 km). According to Column 3, this distance implies a price gap that is 0.056 higher than that between a buyer and seller located within the same municipality of the seller. In contrast, as shown in Table 4 the

[14]For seller-buyer pairs from the same municipality, we assign a distance of 1 kilometer. The distance between the two closest municipalities is 1.3 kilometers. For buyers that purchase the same product from multiple establishments (i.e. unique tax id's appearing on the invoices purchasing a given product from different municipalities), we use the distance to the average establishment (weighted by purchases of the product). Such product-buyer pairs only comprise 10% of purchases in our sample.

cross-buyer range in prices for the median product is 0.28. The within R-squared in Table 7 is less than 1.5% in all specifications, indicating that distance does not account for much of the observed dispersion in price gaps across buyers.

Table 7: Price gaps and differences in costs of supplying different buyers

	(1)	(2)	(3)	(4)	(5)
$\mathbb{I}\,(\log \mathrm{dist}_{ib} = 0)$	-0.0080***	0.0143***	-0.0237***		
	(0.0012)	(0.0012)	(0.0017)		
$\log dist_{ib}$		0.0055***	-0.0144***		
		(0.0001)	(0.0006)		
$(\log dist_{ib})^2$			0.0023***		
			(0.0001)		
$\mathbb{I}_{ib}$ (credit)				-0.0197***	-0.0098***
				(0.0009)	(0.0009)
$\log q_{ib}$					-0.0147***
					(0.0003)
Within R^2	0.0003	0.0089	0.0133	0.0041	0.0300
Observations	3,334,565	3,334,565	3,334,565	2,934,180	2,934,180

Notes: Columns 1-3 reports the results of estimating equation (3) by OLS. Columns 4-5 reports the results of estimating equation (4) by OLS. All columns include product-level fixed effects. Standard errors in parentheses are clustered at the selling establishment-buyer level: * significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

Table 8 uses alternative procedures to isolate the role of distance on the distributions presented in Table 4. Column 2 is based on prices that are first residualized by distance. Column 3 focuses on the sample of invoices in which both the seller and the buyer are located within the city of Santiago. The observed standard deviation of prices is remarkably similar across these subsamples. This suggests that shipping costs are not a significant driver of price dispersion.

Table 8: Price dispersion and distance

	Baseline	Residualized	Santiago
P1	0.00	0.00	0.00
P5	0.00	0.00	0.00
P10	0.01	0.01	0.00
P25	0.02	0.02	0.02
P50	0.06	0.06	0.05
P75	0.10	0.10	0.10
P90	0.16	0.16	0.15
P95	0.21	0.21	0.21
P99	0.35	0.35	0.36
Mean	0.07	0.07	0.07

Notes: The table reports the distribution of the standard deviation of prices across buyers of the same product for different samples. The unit of observation in these distributions is a product i. Column 'Baseline' uses our baseline sample as in Table 4. Column 'Residualized' reports the dispersion in the residuals from the regression Column 3 in Table 7. Column 'Santiago' uses the sample of invoices in which both the seller and the buyer are located within the city of Santiago. The distributions only include products with multiple buyers, and the last row reports the share of sales that correspond to multibuyer products in each sample. P1-P99 represent percentiles of the distribution.

3.2.2 Payment terms

Next, we examine to what extent do price gaps reflect differences in payment terms. To do so, we leverage information on whether the invoice is paid in cash or credit. This information is available for 83% of transactions, accounting for 79% of the sales. Among the transactions for which data on payment terms are available, 68% percent (92% of the sales) are paid in credit. We consider the following price gap regression,[15]

$$\mu_{ib} = \mathbb{I}_{ib}\left(\text{credit}\right) + FE_i + \epsilon_{ib}, \tag{4}$$

where $\mathbb{I}_{ib}\left(\text{credit}\right)$ is a dummy indicating that the buyer b of product i in credit.

Column 4 in Table 7 shows that the coefficient on the indicator variable is negative: price gaps are on average 0.0197 lower when the buyer pays in credit. While this may seem counterintuitive, it may reflect that credit is used for bigger transactions (we examine in more detail the relation between quantities and price gaps in Section 3.4). Indeed, Column 5 shows that the estimated coefficient halves when we include transacted quantity as a control. More importantly, the magnitude of the coefficient is small relative to

[15]We focus on the product-buyer pairs that always exhibit only one payment-term during the month. Buyers that use both cash and credit when purchasing the same product account for only 1.2% of sales.

the observed variation in prices, indicating that the payment terms do not account for the observed price gaps.

3.3 Correlation of price gaps over time

We now evaluate whether price-gaps are persistent. To do so, we regress the price-gap for buyer b paid, product i and month $t =$ June 2022 on the price-gap for the same buyer and product in month $t-k$,[16] controlling for product fixed effects:

$$\mu_{ibt} = \beta_k \mu_{ibt-k} + FE_i + \epsilon_{ib}. \tag{5}$$

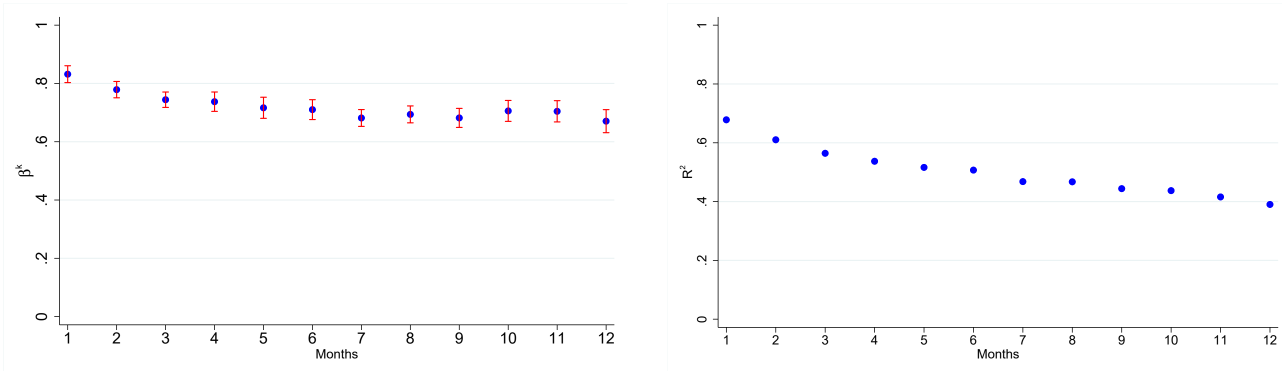
We estimate (5) for lags ranging from 1 to 12 months $(k = 1, ..., 12)$. The coefficient β^k measures the sensitivity of the price gap for a buyer-product in period t to the price gap in $t-k$. The first panel of Figure 1 shows that price gaps are very persistent, with β^k exceeding 0.65 after one year. The second panel of the figure shows that the partial R^2 of this regression is 0.7 for $k = 1$ and drops to 0.4 for $k = 12$. Hence, past levels of price gaps account for most of the variation in current price gaps across buyers of the same product. We obtain similar results in a specification where μ_{ibt} and μ_{ibt-k} are calculated over the subset of product-buyer pairs that exhibit a non-zero price change between t and $t-k$. This suggests that the persistence in price gaps is not driven by nominal price stickiness.

3.4 What drives variation in price gaps?

This section evaluates how price-gaps correlate with observable characteristics of the buyers', the seller-buyer's relation, and the buyer's volume of sales for the product. We begin by showing strong correlations in price gaps across products purchased by the same buyer, and evaluate how price-gaps relate to buyer's size. Then, we show that half of the variance in price gaps is across buyer-seller pairs, and relate price gaps to observable characteristics of the buyer-seller relation. Finally, we show that for a given product, buyers that purchase larger quantities pay lower prices, though quantity discounts do not account for much of the vacation in price gaps in the data.

[16] Since product-level indicators start in June 2021, we use $t =$June 2022 as the dependent variable in this subsection to be able to trace products back in time. Column 5 in Table 5 shows that the price dispersion in June 2022 is very similar to that in June 2021.

Figure 1: Persistence in price gaps



(a) Estimated Coefficients β_k

(b) Partial R-squared

Notes: The left panel plots the coefficients β^k from equation (5) estimated by OLS, for $k = 1, ..., 12$. The regression includes product fixed effects, and observations are weighted by sales. The red lines represent 95 % confidence intervals. The right panel plots the corresponding partial R-squared of the regressions. The corresponding regressions are reported in Appendix Table A.3.

3.4.1 Price gaps and buyer's size

Do buyers face similar price-gaps for different products they purchase? We start by estimating a simple regression of μ_{ib} on product fixed effects and a full set of buyer-level fixed effects for the sample or products with multiple buyers. Column 1 of Table 9 shows that the partial R-squared of this regression is 0.274, indicating that over a quarter of the observed dispersion in price gaps can be accounted for by the identity of the buyers.

Next, we evaluate the relation between price gaps and the buyer's size by fitting regressions of the form:

$$\mu_{ib} = \beta' \text{log} size_b + FE_i + \epsilon_{ib}. \tag{6}$$

Columns 2 and 3 of Table 9 measure size with the buyers' number of employees, Columns 4 and 5 with the buyers' total sales, and Columns 6 and 7 with the buyers' purchases of intermediate inputs. We can observe that, for the three different measures of size, larger buyers tend to pay lower prices, though the effects are non-linear. We note, however, that the within R-squared in Columns 2-7 is a tiny fraction of that in Column 1. This indicates that, whereas the buyer identity explains a sizable share of price gaps across buyers, the buyer's size is not a major characteristic explaining these price gaps.

Table 9: Price gaps and buyer size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\log \text{emp}_b$		-0.0015*	-0.0041***				
		(0.0007)	(0.0006)				
$(\log \text{emp}_b)^2$			0.0005*				
			(0.0002)				
$\log \text{sales}_b$				-0.0023***	-0.0242***		
				(0.0007)	(0.0043)		
$(\log \text{sales}_b)^2$					0.0005***		
					(0.0001)		
$\log \text{purch}_b$						-0.0037***	-0.0350***
						(0.0009)	(0.0034)
$(\log \text{purch}_b)^2$							0.0009***
							(0.0001)
Partial R2	0.274	0.0007	0.0022	0.0022	0.0054	0.0046	0.0124
Observations	3,349,120	3,349,120	3,349,120	3,349,120	3,349,120	3,349,120	3,349,120
Buyer FE	Yes	No	No	No	No	No	No

Notes: The table reports the results of estimating equation (6) by OLS. All columns include product-level fixed effects. emp_b, sales_b, and purch_b respectively denote the employment, sales, and intermediate input purchases of buyer b. Standard errors in parentheses are clustered at the buyer level * significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

3.4.2 Price gaps and buyer-seller relations

Are price gaps correlated across products within buyer-seller pairs? Column 1 of Table 10 fits a regression of μ_{ib} on product fixed effects and a full set of seller-buyer fixed effects. In order to be included in this regression, buyer-sellers must transact in more than one product. The partial R-squared of this regression is 0.5, indicating that buyer-seller dummies account for half of the residual variation in price gaps.

We evaluate the relation between price gaps and observable characteristics of buyer-seller pairs by fitting regressions of the form

$$\mu_{ib} = \beta' \mathbf{X}_{s(i)b} + FE_i + \epsilon_{ib}, \tag{7}$$

where $\mathbf{X}_{s(i)b}$ contains observable characteristics of the relation between the buyer b and the seller of product i.

We first evaluate how price gaps vary with the length of the relation between the seller and the buyer. Define the length of the relation between buyer b and the seller of product

i as the number of months since the first observed transaction between these two firms in our dataset. We construct dummy variables indicating whether the relation is new (no previous transactions), started over the prior year, or is longer than a year. Column 2 in Table 10 shows a regression of price gaps on these dummies, where the omitted category is new relations. Price gaps for new relations are 0.019 points higher than for relations that started during the previous year, and 0.024 higher than for relations that are older than a year.

Columns 3 and 4 display the relation between price gaps and total sales of the seller of product i to buyer b. Price gaps are lower in buyer-seller pairs with higher sales, though the relation is non-linear. Finally, Column 5 shows partial elasticities when these observable characteristics are included simultaneously in the regression. We observe that the within R-squared in Columns 5 is small relative to that of Column 1, showing that while these correlations are statistically significant, they only account for a small fraction of the differences price gaps across buyer-seller pairs.

Table 10: Price gaps and characteristics of the buyer-seller relation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
relation < 1 yr		-0.0191***			-0.0152***			
		(0.0010)			(0.0010)			
relation $\geq$ 1 yr		-0.0244***			-0.0166***			
		(0.0011)			(0.0010)			
log $sales_{s(i)b}$			-0.0073***	-0.0250***	-0.0246***			
			(0.0005)	(0.0031)	(0.0031)			
$\left(\log sales_{s(i)b}\right)^2$				0.0006***	0.0006***			
				(0.0001)	(0.0001)			
$\log q_{ib}$						-0.0071***	-0.0095***	-0.0067***
						(0.0011)	(0.0002)	(0.0003)
$(\log q_{ib})^2$								-0.0005***
								(0.0001)
Partial R2	0.504	0.0021	0.0130	0.0153	0.0161	0.0067	0.509	0.510
Observations	3,271,243	3,271,243	3,271,243	3,271,243	3,271,243	3,375,849	3,271,243	3,271,243
Buyer-Seller FE	Yes	No	No	No	No	No	Yes	Yes

Notes: Columns 1-5 report the results of estimating equation (10) by OLS. All columns include product-level fixed effects. "relation < 1 yr" and "relation $\geq$ 1 yr" respectively denote indicator variables for whether the first recorded transaction in the data for the corresponding seller-buyer pair occurred over June 2020-May 2021, and before June 2021. $sales_{s(i)b}$ are the total sales of the seller of product i to buyer b. Columns 6 and 7 report the results of regressions of the form $\mu_{ib} = \beta' \log q_{ib} + FE_{s(i)b} + \epsilon_{ib}$. Standard errors in parentheses are clustered at the seller-buyer level. * significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

3.4.3 Price gaps and quantity discounts

Finally, we evaluate the relation between price gaps and quantity purchased across buyers. We begin by fitting a regression of price gaps on product-buyer quantities, including product fixed effects. Columns 6 of Table 10 shows that buyers purchasing larger quantities of a product face lower price gaps. However, the low partial R-squared of this regression reveals that variation in the volume of purchases across buyers account for a small fraction of the variation price gaps. [17]

Next, we examine whether, within buyer-seller relations, price gaps vary with the purchased quantity of the product. We fit a regression of prices on quantities, including both product and buyer-seller fixed effects. In order to be included in this regression,

[17] For the median product, the observed range in log quantities purchased by different buyers is 1.95 points, which according to the estimates in Column 2 implies a difference in log prices of only 0.02. In contrast, the median range in prices is 0.28.

buyer-sellers must transact in more than one product. Columns 7 and 8 of Table 10 show that for a given product, buyers that purchase larger quantities pay lower prices. The relation is non-linear, and is not economically significant. Finally, the partial R-squared displayed in Column 8 is similar to that in Column 1, indicating that quantities do not explain much of the residual (after taking out the buyer-seller fixed effect) variation in price gaps.

3.5 Price-quantity menus

In Section 4 we will quantify the productivity losses arising from variation in prices across buyers. We will make the assumption that buyers can purchase any desired quantity of an input at the transacted price. An alternative assumption is that sellers engage in second- or third-degree price discrimination, offering menus of quantities and prices. In this case, prices are not allocative other than by making certain menus more attractive to some buyers, and price gaps are not informative of misallocation.

The assumption of fixed menus implies a one-to-one mapping between quantities and prices. One testable implication of this assumption is that variation in quantities should entirely account for variation in prices. The low within R-squared in the regressions presented in Table 10 already suggests that this is not the case. However, changes in prices and quantities may reflect other shocks that make producers change the menu they offer.

To test the hypothesis of non-linear prices set by sellers to individual buyers, we examine whether across transactions of a particular product-buyer pair, a given price is associated to the same quantity. Specifically, using the transaction-level data, we compute for each product-buyer pair the standard deviation of log prices and log quantities across transactions that occurred in June 2021. The first column in Table 11 reports the standard deviation of quantities for the product-buyer pairs that have a standard deviation of prices that is less than 1%. If quantity-price menus are prevalent, we should observe a small dispersion of quantities across observations. Instead, we observe substantial dispersion in quantities among these buyers that consistently pay the same price across transactions.

The second column of Table 11 reports log changes in quantities for each product-buyer pair in the period June-July 2021, considering only pairs of transactions that experienced a price change smaller than 1% during that period. Again, we observe large changes in quantities associated with product-buyer pairs with small price movements. These results suggest that fixed price-quantity menus between buyers and sellers are not prevalent in our data. Of course, this evidence is not inconsistent with price discrimination by producers across sellers, which is the focus of the paper.

Table 11: Quantity-price menus

	$\text{stdev}_{ib}(\log q_{ib\tau})$	$\lvert\log q_{ibt+1} - \log q_{ibt}\rvert$
p1	0.00	0.00
p5	0.00	0.01
p10	0.00	0.02
p25	0.01	0.11
p50	0.35	0.31
p75	0.58	0.69
p90	0.79	1.28
p95	0.97	1.74
p99	1.55	3.14
Mean	0.38	0.53

Notes: The first column reports the distribution of the standard deviation of quantities across transaction for a given product-buyer pair, in which the standard deviation of prices is less than 0.01. The distribution excludes product-buyer pairs that record only one transaction. The second column reports the distribution of the log-change in quantities for each product-buyer pair between June and July 2021, for pairs that experienced a price change of less than 1% during the period. The unit of observation in these distributions is a product-buyer pair *ib*. The distributions are sales weighted.

3.6 Taking stock

The results from the last two sections reveal a novel set facts about how prices of intermediate inputs vary across buyers. First, there is substantial dispersion in the prices that different buyers pay for the same input, even across transactions occurring within the same month. This dispersion in prices is pervasive across manufacturing sectors, and is more pronounced for products with higher sales, sold by larger sellers, and purchased by a larger number of buyers.

Second, the observed price gaps are highly persistent over time, strongly correlated across different products purchased by the same buyer. Prices are lower for larger buyers, for buyer-seller pairs with older relations and higher volume of sales, and are decreasing in the volume of purchased quantities. However, these observed characteristics of the buyer, seller, and transacted quantities account for a small fraction of the variation in price gaps. We also establish that price gaps are not driven by transportation costs, nominal price stickiness, or by sellers offering fixed quantity-price menus for the same product.

These facts motivate the framework that we use in the next section to quantify the welfare costs of price dispersion for identical products across buyers. The framework interprets price gaps as differences in markups rather than as differences in the cost of supplying different buyers. We model these price gaps as exogenous wedges. Any model of endogenous wedges would have to confront the observation that buyer-seller relationships account for a significant portion of the observed price gaps, but observed characteristics (such as buyer or seller size size and transacted quantity) do not. In the model, we assume that the price gaps are allocative and that buyers can purchase any desired quantity of an input at the observed prices.

4 Model

This section presents a theoretical framework to quantify the welfare costs of markup dispersion across buyers.

Preliminaries: We consider a closed economy with J sectors indexed by j, each populated by a discrete number of firms. Firms produce differentiated products, indexed by i, using a fixed factor L and a bundle of intermediate inputs. Firms products are the sold to other firms or to final consumers. A firm can potentially produce multiple products. Markups are exogenous and can differ across products and buyers.

Technologies final goods: There is a final consumption good in the economy that is produced by aggregating the output from the different sectors:

$$C = \left[\sum_j \left[\bar{\gamma}^j \right]^{\frac{1}{\eta}} \left[C^j \right]^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}.$$

Here C^j is a sectorial aggregate given by

$$C^j = \left[\sum_{i \in j} \bar{\gamma}_i^{\frac{1}{\rho}} c_i^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}},$$

where c_i denotes the quantity of product i used by the final good producer.

Technologies intermediate products: The production function for product i is given by:

$$y_i = z_i b_i,$$

where b_i is a bundle of inputs given by

$$b_i = \left[[1-\bar{\alpha}_i]^{\frac{1}{\sigma}} l_i^{\frac{\sigma-1}{\sigma}} + \bar{\alpha}_i^{\frac{1}{\sigma}} m_i^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}.$$

Here l_i denotes use of the fixed factor, and m_i is a bundle of intermediate inputs:

$$m_i = \left[\sum_j \left[\bar{\omega}_i^j\right]^{\frac{1}{\eta}} \left[m_i^j\right]^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}},$$

with

$$m_i^j = \left[\sum_{i' \in j} \bar{\omega}_{i'i}^{\frac{1}{\rho}} x_{i'i}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}},$$

where $x_{i'i}$ denotes the quantity of product i' used in the production of i.

Market clearing: Goods market clearing implies:

$$y_i = c_i + \sum_{i'} x_{ii'} \qquad \forall i, \tag{8}$$

and factor market clearing implies

$$\sum_i l_i = \bar{L}. \tag{9}$$

Prices and wedges: Let $p_{ii'}$ and and p_{ic} respectively denote the price of product i when sold to i' and when sold to final consumers. These prices are given by:

$$p_{ii'} = \mu_{ii'} mc_i; \quad p_{ic} = \mu_{ic} mc_i, \tag{10}$$

where μ_{ii} and μ_{ic} are exogenous markups and mc_i is the marginal cost of production for product i.

Equilibrium: Given technologies and wedges $\{\mu_{ii}, \mu_{ic}\}$, an equilibrium is a set of prices $\{p_{ii'}, p_{ic}\}$, factor prices $\{w\}$, intermediate input choices $x_{ii'}$, factor choices l_i, outputs y_i, and final demands c_i, such that (i) firms minimize costs and set prices to $p_{ii'} = \mu_{ii'} mc_i$ and $p_{ic} = \mu_{ic} mc_i$; (ii) final producers minimize costs; and (iii) all markets clear.

We characterize the equilibrium and in Appendix C.

4.1 Response to changes in markups

We now evaluate how equilibrium prices and quantities change in response to exogenous changes in markups. We use the notation $\hat{X} \equiv \frac{X_1}{X_0}$ to denote the ratio of a variable in the new relative to the initial equilibrium. The changes in product level prices can be written as:

$$\hat{p}_{ii'} = \hat{\mu}_{ii'}\widehat{mc}_i; \quad \hat{p}_{ic} = \hat{\mu}_{ic}\widehat{mc}_i, \tag{11}$$

with

$$\widehat{mc}_i = \left[1 - \alpha_i + \alpha_i \hat{q}_i^{1-\sigma}\right]^{\frac{1}{1-\sigma}}. \tag{12}$$

Here, $\alpha_i \equiv \frac{q_i m_i}{l_i + q_i m_i}$ is the cost share of materials for product i, and the price of the composite factor is the numeraire. q_i is the price of the input bundle used in the production of i:

$$\hat{q}_i = \left[\sum_j \omega_i^j \left[\hat{q}_i^j\right]^{1-\eta}\right]^{\frac{1}{1-\eta}}; \quad \hat{q}_i^j = \left[\frac{1}{\omega_i^j} \sum_{i' \in j} \omega_{i'i} \hat{p}_{i'i}^{1-\rho}\right]^{\frac{1}{1-\rho}}, \tag{13}$$

with $\omega_{i'i} \equiv \dfrac{p_{i'i} x_{i'i}}{q_i m_i}$ and $\omega_i^j \equiv \sum_{i' \in j} \omega_{i'i}$. Changes in final good prices are given by:

$$\hat{P} = \left[\sum_j s^{jc} \left[\hat{P}^j\right]^{1-\eta}\right]^{\frac{1}{1-\eta}}; \quad \hat{P}^j = \left[\frac{1}{s^{jc}} \sum_{i \in j} s_i^c \hat{p}_{ic}^{1-\rho}\right]^{\frac{1}{1-\rho}}. \tag{14}$$

with $s_i^c \equiv \frac{p_{ic} c_i}{\sum_i p_{ic} c_i}$ and $s^{jc} \equiv \sum_{i \in j} s_i^c$.

Finally, goods market clearing implies:

$$\hat{y}_i = \frac{c_i}{y_i} \hat{p}_{ic}^{-\rho} \left[\hat{P}^j\right]^{\rho-\eta} \hat{P}^\eta \hat{C} + \left[1 - \frac{c_i}{y_i}\right] \sum_{i'} s_{ii'} \hat{p}_{ii'}^{-\rho} \left[\hat{q}_{i'}^j\right]^{\rho-\eta} \hat{q}_{i'}^{\eta-\sigma} \widehat{mc}_{i'}^{\sigma} \hat{y}_{i'}, \qquad \forall i \tag{15}$$

where $s_{ii'} \equiv x_{ii'} / \sum_{i'} x_{ii'}$. Factor market clearing implies

$$1 = \sum_i s_i^l \widehat{mc}_i^{\sigma} \hat{y}_i. \tag{16}$$

with $s_i^l \equiv l_i / L$.

4.2 Theoretical results

We now evaluate the welfare change from eliminating markup dispersion across buyers in the special case of a vertical network. In particular, we assume that there are two sectors which we label u and d (upstream and downstream). Products in u only use the composite factor for production and are only sold to the d sector: $\alpha_i = 0$ and $c_i/y_i = 0$ for $i \in u$. Conversely, products in d only use intermediate inputs and are only sold to final consumers: $\alpha_i = 1$ and $c_i/y_i = 1$ for $i \in d$.

We are interested in evaluating the response of eliminating dispersion in markup across buyers of the same input. Let $\mathcal{M}_i \equiv \sum_{i'} \mu_{ii'} s_{ii'}$ denote the quantity/cost weighted average markup of product i in the initial equilibrium. In our counterfactual, we evaluate the changes in markups $\hat{\mu}_{ii'} = \frac{\mathcal{M}_i}{\mu_{ii'}}$ for $i \in u$, and keep the markups of d products unchanged, $\hat{\mu}_{ic} = 1$ for $i \in d$.

Appendix C shows that under these assumptions, changes in markups result in the following change in final consumption:

$$\hat{C} = \left[\sum_{i \in u} s_i^x \frac{\overline{\mathcal{M}_u}}{\mathcal{M}_i} \sum_{i' \in d} s_{ii'} \hat{\mu}_{ii'}^{-\rho} \right]^{-1} \left[\sum_{i \in u} s_i^x \sum_{i' \in d} \frac{\mathcal{M}_{i'}}{\overline{\mathcal{M}_d}} s_{ii'} \hat{\mu}_{ii'}^{-\rho} \right]^{\frac{\rho}{\rho-1}},$$

where $\overline{\mathcal{M}_k}$ is the average markup in sector k and $s_i^x \equiv \frac{\sum_{i'} p_{ii'} x_{ii'}}{\sum_{i \in u} \sum_{i'} p_{ii'} x_{ii'}}$ is the share of input i in total input sales. If markups are common across products within sectors we obtain

$$\hat{C} = \left[\sum_{i \in u} s_i^x \xi_i \right]^{\frac{1}{\rho-1}},$$

where

$$\xi_i \equiv \frac{\sum_{i'} s_{ii'} \mu_{ii'}^{\rho}}{\left[\sum_{i'} s_{ii'} \mu_{ii'} \right]^{\rho}} \geq 1 \quad \text{if } \rho > 1.$$

Note that $\xi_i > 1$ and $\hat{C} > 1$ if markups $\mu_{ii'}$ are dispersed across buyers i' and $\rho > 1$. In addition, $\hat{C}$ increases with both the dispersion in markups and with the elasticity.

5 Quantitative results

5.1 Mapping the model to data

This section describes how we quantify the welfare gains from equating markups across buyers using the price data from the Chilean electronic invoices.

5.1.1 Measuring dispersion in markups across buyers

Our quantitative exercise is based on the fact that, if marginal costs of production do not depend on the buyers' identities, differences in markups across buyers can be measured from observed differences in prices. That is, under the assumption that mc_i is the same for all b, we can use price data at the product-buyer level to compute:

$$\hat{\mu}_{ii'} = \frac{\sum_b \mu_{ib} s_{ib}}{\mu_{ii'}} = \frac{\sum_b \mu_{ib} mc_i s_{ib}}{\mu_{ii'} mc_i} = \frac{\sum_{ib} p_{ib} s_{ib}}{p_{ii'}}. \tag{17}$$

We will use the price data presented in Section 2 to compute (17) for the products i for which we identify unique codes. Note that the prices p_{ib} are available for all buyers b observed in the invoices, regardless of whether the buyer uses product codes when emitting invoices. In our baseline exercise, we focus on the network of products for which we observe product identifiers, and additionally include all the buyers of these products in both the manufacturing and retail sectors, and firms with at least 5 full-time workers.With this in mind, we divide products into two sets: those that have product codes and can be identified as unique, $i \in S$, and those that do not, $i \notin S$. In our counterfactual exercises, we change markups for products $i \in S$ according to (17), and keep markups for products $i \notin S$ constant, $\hat{\mu}_{ii'} = 1$. We also keep markups for all final sales constant, $\hat{\mu}_{ic} = 1$.

5.1.2 Network statistics

The characteristics of the resulting network are summarized in Appendix Table A.4. There are 189,947 products and 18,292 firms in the network. This results in more than 3 billion possible product-buyer pairs, for which we observe positive sales for 876,852. The counterfactual exercise thus requires solving a large fixed point problem. Appendix C describes our solution algorithm.

Products in $i \in S$ account for 36% of total sales. As previously mentioned, our counterfactual exercise will only modify the markups for firm-to-firm sales of the products in $i \in S$. These particular sales account for 17% of the total sales. Half of these sales involve products with multiple buyers, meaning that we will adjust markups for 8% of the overall sales in the economy.

5.1.3 Parameterization

To evaluate how changes in markups affect the system in Section 4.1, we need to assign values to the cost share of inputs, α_i, the share of each input i' in input expenditures, $\omega_{i'i}$, the share of the fixed factors used for the production of each product, s_i^l, the share of each product in final sales, s_i^c, and the fraction of the product that is sold to final consumers and to each other intermediate product i', $\frac{c_i}{y_i}$ and $s_{ii'}$. We also need to assign values to the elasticities of substitution between factors and materials σ, and the elasticities of substitution across products and sectors, ρ and η.

Rather than making distributional assumptions to calibrate the shares, we map each product in the model to a product in the Chilean data. A challenge arises due to the fact that, while most firms in the data sell multiple products, input use data is only available at the firm level. Furthermore, the invoices identify the buyer of each input, but not how buyers apportion inputs across their multiple products.[18] To apportion firm-level inputs to products, we assume a firm uses the same input bundle and sets the same average markup across its multiple products. Appendix C shows that under these assumptions, we can apportion firms' inputs across products in proportion to sales.

We calibrate the shares by complementing the data from the invoices with income declaration forms collected by the Chilean tax authority (form 22 or IDF), which provide firm-level data on input expenditures, total costs, and value added. Since we do not include every invoice in the model's network, we treat purchases of inputs not in the network as purchases of the fixed factor.[19] We use θ_f to denote the share of input purchases of firm f that is included in the model's network. Also, we use $f(i)$ to denote the identity of the firm that produces product i, and $\kappa_i \equiv \left[\sum_b p_{ib}x_{ib}\right] / \left[\sum_{i \in f(i)} \sum_b p_{ib}x_{ib}\right]$ to denote the share of product i in firm's $f(i)$ sales.

We can now assign values to the model's parameters. To calibrate α_i, we take the ratio of input expenditures to total costs of firm $f(i)$ from the income declaration form, and multiply it by the share of input purchases included in the network, $\theta_{f(i)}$. We compute $\omega_{i'i}$ as the ratio of purchases of product i' relative to all input purchases by firm $f(i)$ from

[18] That is, the invoices have data on prices and quantities at the product-buyer level p_{ib} and x_{ib}, where the buyer b is identified by its tax ID.

[19] As noted above, we focus on the network of products for which we observe product identifiers, and additionally include all the buyers of these products in both the manufacturing and retail sectors. This implies that, for example, purchases of agricultural inputs are not considered in the network and are lumped with the fixed factor.

the invoices. We also obtain $s_{ii'}$ as the product of the quantity share of product i that goes to firm $f(i')$, $\frac{x_{if(i')}}{\sum_{f'} x_{if'}}$, and the share of product i' in $f(i')$ sales, $s_{ii'} \equiv \frac{x_{if(i')}}{\sum_{f'} x_{if'}} \times \kappa_i$.

We obtain the remaining shares after first calibrating the following auxiliary variables. First, we use the invoices to compute the share of each product i in total intermediate input sales, $s_i^x \equiv \left[\sum_{i'} p_{ii'} x_{ii'}\right] / \left[\sum_i \sum_{i'} p_{ii'} x_{ii'}\right]$, and the share of each firm in total intermediate input purchases, $s_f^m \equiv \left[\sum_i p_{if} x_{if}\right] / \left[\sum_f \sum_i p_{if} x_{if}\right]$. We then compute the share of product i in total intermediate input purchases as $s_i^m = s_{f(i)}^m \times k_i$. Second, we compute the ratio of value added to revenues for each product i, which we denote by v_i. While this ratio can be obtained from the income declaration forms, for positive prices and quantities, it must satisfy $1 - v_i = \frac{\sum_{i'} p_{i'i} x_{i'i}}{p_{ic} c_i + \sum_{i'} p_{ii'} x_{ii'}} \leq \frac{\sum_{i'} p_{i'i} x_{i'i}}{\sum_{i'} p_{ii'} x_{ii'}} = \frac{s_i^m}{s_i^x}$. We thus compute the ratio of input purchases to revenues in the income declaration forms and set $1 - v_i = \min \left\{ \frac{inputs_{f(i)}^{IDF} \times \theta_{f(i)}}{revenue_{f(i)}^{IDF}}, 1 - \frac{s_i^m}{s_i^x} \right\}$.

We then obtain the remaining shares by setting $s_i^c = \left[s_i^m \frac{1}{1-v_i} - s_i^x \right] \frac{1-v}{v}$, $s_i^l = \left[\frac{1-\alpha_i}{\alpha_i} / \frac{1-\alpha}{\alpha} \right] s_i^m$, and $\frac{c_i}{y_i} = \left[1 + \frac{1-v}{v} \frac{s_i^x}{\gamma_i} \right]^{-1}$. Here v and α respectively denote the economy-wide ratio of value added to revenues, and the economy-wide ratio of input purchases to total cost. Using the previously targeted shares, we obtain these ratios as $v = \left[\sum_i s_i^m / v_i \right]^{-1} = 0.65$ and $\alpha = \left[\sum_i s_i^m / \alpha_i \right]^{-1} = 0.39$. We note that the calibration implies a ratio of revenues to costs equal to $\frac{\text{revenues}_\text{i}}{\text{cost}_\text{i}} = \frac{\alpha_i}{1-v_i}$. Therefore, the ratio of total revenues to total costs in the economy is $\frac{\alpha}{1-\nu} = 1.11$. Table 12 summarizes the calibration of the initial shares.

Finally, we assume the production function is Cobb-Douglas between fixed factors and the input bundle, and set $\sigma = 1$. We also assume single sector and set $\rho = \eta$. We evaluate below how these assumptions shape the quantitative exercise. We also consider different values for the elasticity across products, ρ.

Table 12: Calibration of initial shares

Targeted shares

α_i	Ratio of purchases of input to total cost of firm $f(i)$, IDF, EI.
$\omega_{i'i}$	Share of intermediate input i' in input purchases of firm $f(i)$, EI.
s_i^x	Share of input i in total intermediate input sales, EI.
κ_i	Share of product i in firm's $f(i)$ sales, EI.
$s_{ii'}$	Quantity share of intermediate of i going to $f(i')$ multiplied by κ_i, EI.
s_i^m	Share of $f(i)$ in total intermediate input purchases multiplied by κ_i, EI.
v_i	Ratio value added to revenues of firm $f(i)$. IDF, EI.

Non targeted shares

s_i^c	Share of sales product i in total final sales: $s_i^c = \left[s_i^m \frac{1}{1-v_i} - s_i^x\right] \frac{1-v}{v}$.
s_i^l	Share of the fixed factor that is used for the production of i: $s_i^l = \left[\frac{1-\alpha_i}{\alpha_i} / \frac{1-\alpha}{\alpha}\right] s_i^m$.
$\frac{c_i}{y_i}$	Fraction of good i that is sold to final consumers: $\frac{c_i}{y_i} = \left[1 + \frac{1-v}{v} \frac{s_i^x}{s_i^c}\right]^{-1}$.
α	Economy wide share of inputs in production cost: $\alpha \equiv \left[\sum_i s_i^m / \alpha_i\right]^{-1} = 0.39$
v	Economy wide ratio of value added to revenues. $v \equiv \left[\sum_i s_i^m / v_i\right]^{-1} = 0.65$

Notes: This table describes how we assign values to the model's initial shares under our baseline calibration. $f(i)$ refers to the firm (tax id) that sells product i. 'EI' and 'IDF'; indicate that calculations are based on data sourced from the Electronic Invoices and from the Income Declaration Forms respectively.

5.2 Eliminating markup dispersion across buyers

Table 13 presents the results from the counterfactual exercise. The first row reports the results under our baseline calibration and baseline definition of products. Column 2 reports the counterfactual change in welfare when $\rho = 3$, which is given by $\hat{C} - 1 = 0.17\%$. To put this magnitude into perspective, it's important to consider that we are only changing markups for 8% of the total sales. Normalizing the change in welfare by the fraction of sales with changed markups we obtain a value of 2.23% as reported in Column 3. Columns 4 and 5 present results for $\rho = 6$, showing a normalized change in welfare of 7.27%.

The second row reports results under the EAN definition of products. Since only a small fraction of products use EAN codes, the fraction of shocked sales in this exercise drops to 3%. The normalized change in welfare in this exercise is however larger than in the baseline, 3.21% for $\rho = 3$ and 10.56% for $\rho = 6$. This reflects that EAN products, on average, have a higher number of buyers and more dispersed prices across these buyers compared to the products classified in our baseline.

Row 3 reports results using our baseline definition of products but restricting the sample to sellers and buyers located within the city of Santiago. As discussed in Section 2, the assumption that the marginal cost of production is independent of the buyer's identity is more likely to hold when the seller and the buyer are within the same city, as this minimizes potential differences in delivery costs across buyers. The resulting changes in normalized welfare are similar to those our baseline sample when we set $\rho = 3$ (1.82% vs. 2.23%), though the difference is magnified if we set $\rho = 6$ (4.48% vs. 7.27%).

The last two rows show results for alternative values of the production elasticities σ and η. In Row 4, we divide the products $i \in S$ and $i \notin S$ into two different sectors, and set the elasticity across sectors to $\eta = 1$. Lowering this elasticity leads to a somewhat larger counterfactual change in normalized welfare (2.41% vs. 2.23% when $\rho = 3$). In Row 5 we lower the elasticity of substitution between factors and materials to $\sigma = 0.5$. This parameterization results in a smaller counterfactual change in welfare compared to the baseline (1.68% vs. 2.23% when $\rho = 3$). Overall, our baseline results do not appear to be very sensitivity to plausible changes in these two elasticities.

Table 13: Welfare gains from eliminating markup dispersion across buyers

	shocked sales / total sales	Low elasticity: $\rho = 3$		High elasticity: $\rho = 6$	
		welfare (%)	(2)/(1)	welfare (%)	(4)/(1)
	(1)	(2)	(3)	(4)	(5)
Baseline	0.08	0.17	2.23	0.56	7.27
EAN	0.03	0.10	3.21	0.35	10.56
Santiago	0.08	0.14	1.82	0.34	4.48
$\eta = 1$	0.08	0.18	2.41	0.62	8.05
$\sigma = 0.5$	0.08	0.13	1.68	0.44	5.76

Notes: This table reports the results of our counterfactual that eliminates the dispersion in markups across buyers of a given input. 'Baseline' refers to our baseline calibration. 'EAN' refers to a network that comprises the EAN products all the buyers of EAN products that are in the manufacturing and the retail sectors. 'Santiago' uses our baseline calibration but limits the network to products and firms located in Santiago. '$\eta = 1$' divides our sample of products into two sectors $i \in S$ and $i \notin S$, and sets $\eta = 1$. The last row follows our baseline calibration but sets $\sigma = 0.5$.

5.2.1 Eliminating markup dispersion across products

We now compare the gains from eliminating markup dispersion across buyers with the gains from eliminating markup dispersion across buyers and products. In particular, for products in $i \in S$ with multiple buyers, we set the counterfactual markup equal to the economy-wide ratio of revenues to costs. For these products, the change in markups is

$$\hat{\mu}_{ii'} = \frac{\mathcal{M}_i}{\mu_{ii'}} \times \frac{\mathcal{M}}{\mathcal{M}_i}.$$

The first ratio in the right hand side is the change of setting the markup $\mu_{ii'}$ equal to the average markup of product i, $\mathcal{M}_i$. We can obtain this ratio from the invoices as described in equation (17). The second ratio is the result of setting the product level markup, $\mathcal{M}_i$, equal to the economy wide markup, $\mathcal{M}$. We target $\mathcal{M}_i$ directly to match as the ratio of revenues to cost in the income declaration forms for firm $f(i)$. We also set $\mathcal{M} \equiv \left[\sum_i \mathcal{M}_i^{-1} s_i^r\right]^{-1}$, where $s_i^r = v s_i^c + [1 - v]\, s_i^x$ is the share of product i in aggregate sales.

We note again that our model implies that the ratio of revenues to cost for each product should equal $\frac{\alpha_i}{1-v_i}$. To be able to target $\mathcal{M}_i$ directly without changing the distribution of product sales and purchases, we set $\alpha_i = \mathcal{M}_i \times [1 - v_i]$ for this exercise.[20] As our goal is to compare this counterfactual with our baseline exercise, we do not change markups for other products nor markups to final sales and set $\hat{\mu}_{ii'} = 1$ and $\hat{\mu}_{ic} = 1$.

Table 14 presents the results. The first row repeats the baseline counterfactual in Table 13 using the new calibration that targets $\mathcal{M}_i$ rather than α_i. Reassuringly, the results of the first counterfactual are not much affected by this change in the calibration. The second row shows the results of eliminating the dispersion in markups both across buyers and across products. This counterfactual yields a normalized welfare gain of 5.46% in the case of $\rho = 3$, and of 14.79% in the case of $\rho = 6$. These gains are slightly more than twice the gains from eliminating the dispersion across buyers alone, indicating that the dispersion across buyers is almost as costly as the dispersion in markups across products in our sample.

[20] Note that in our baseline calibration, $s_i^c = \left[s_i^m \frac{1}{1-v_i} - s_i^x\right] \frac{1-v}{v}$. To keep s_i^c, s_i^x, and s_i^m unchanged, v_i must be unchanged, so in this exercise we set $\alpha_i = \mathcal{M}_i \times [1 - v_i]$ to target $\mathcal{M}_i$. This recalibration only affects products with $\frac{inputs_{f(i)}^{IDF} \times \theta_{f(i)}}{revenue_{f(i)}^{IDF}} > \frac{s_i^m}{s_i^x}$. For products where $\frac{inputs_{f(i)}^{IDF} \times \theta_{f(i)}}{revenue_{f(i)}^{IDF}} < \frac{s_i^m}{s_i^x}$, we have that $\alpha_i = \mathcal{M}_i \times [1 - v_i] = \frac{revenue_{f(i)}^{IDF}}{cost_{f(i)}^{IDF}} \times \frac{inputs_{f(i)}^{IDF} \times \theta_{f(i)}}{revenue_{f(i)}^{IDF}} = \frac{inputs_{f(i)}^{IDF}}{cost_{f(i)}^{IDF}} \times \theta_{f(i)}$, which coincides with the calibration of α_i described in the previous section.

Table 14: Welfare gains from eliminating markup dispersion across buyers and products

	shocked sales / total sales	Low elasticity: $\rho = 3$		High elasticity: $\rho = 6$	
		welfare (%)	(2)/(1)	welfare (%)	(4)/(1)
	(1)	(2)	(3)	(4)	(5)
Counterfactual 1*	0.08	0.18	2.40	0.51	6.63
Counterfactual 2	0.08	0.42	5.46	1.14	14.79

Notes: 'Counterfactual 1*' reports results from the counterfactual that eliminates the dispersion in markups across buyers of a given input, but using a calibration that directly targets $\mathcal{M}_i$ rather than α_i. 'Counterfactual 2' reports results from the counterfactual that eliminates the dispersion in markups across buyers of a given input and also across inputs under that same calibration.

6 Conclusion

Using a comprehensive dataset of electronic invoices issued by Chilean firms, we document pervasive dispersion in the prices that different buyers pay for the same intermediate goods. While prices are negatively correlated to different measures of the buyer's and transaction's size, observable characteristics of products and of buyer-seller pairs explain only a small fraction of the variance of price gaps in the data. The observed price-gaps do not appear to reflect differences in the terms of payment nor in the cost of supplying different buyers. Using a workhorse model of production networks that infers differences in buyer-specific markups from the observed price dispersion, we show that the gains from eliminating markup dispersion across buyers are of magnitude as large as those of eliminating markup dispersion across products.

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Appendix

A Additional tables and figures

Table A.1: Price dispersion by sector

	σ_i															
	Food	Beverages	Textiles, Shoes	Wood prod-ucts	Paper	Printing	Chemicals	Pharma ceutical	Plastic, Rubber	Non-metallic minerals	Metals	Metal prod-ucts	Electric equip	Machinery and equip	Furniture	Other
P1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P5	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00
P10	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.02	0.01	0.01	0.00	0.00	0.00
P25	0.03	0.00	0.01	0.02	0.01	0.02	0.03	0.02	0.02	0.04	0.04	0.02	0.02	0.01	0.02	0.03
P50	0.06	0.02	0.04	0.03	0.08	0.05	0.07	0.07	0.06	0.06	0.07	0.06	0.03	0.04	0.02	0.05
P75	0.10	0.08	0.07	0.07	0.14	0.09	0.12	0.14	0.11	0.10	0.09	0.10	0.06	0.08	0.04	0.10
P90	0.14	0.13	0.14	0.09	0.22	0.22	0.20	0.26	0.16	0.13	0.11	0.17	0.11	0.14	0.11	0.19
P95	0.17	0.18	0.21	0.13	0.27	0.32	0.26	0.34	0.21	0.17	0.13	0.25	0.15	0.25	0.13	0.29
P99	0.27	0.26	0.37	0.28	0.39	0.45	0.38	0.51	0.30	0.24	0.25	0.37	0.27	0.42	0.32	0.54
Mean	0.07	0.05	0.06	0.05	0.10	0.08	0.09	0.10	0.08	0.07	0.07	0.08	0.05	0.07	0.04	0.08
Share multibuyer	0.50	0.61	0.59	0.66	0.55	0.33	0.56	0.78	0.41	0.73	0.82	0.44	0.77	0.27	0.46	0.32

Notes: The table reports the distribution of the standard deviation of prices across buyers of the same product within the different manufacturing subsectors in our baseline sample. The distributions are based on the subsample or products that were purchased by more than one buyer in June 2021. 'Share multibuyer' relers to the share of subsector's sales that is acconted for by products that ere purchsed by more than one buyer.

Table A.2: Price dispersion and seller size

	σ_i			
	Q1	Q2	Q3	Q4
P1	0.00	0.00	0.00	0.00
P5	0.00	0.00	0.00	0.01
P10	0.00	0.01	0.01	0.01
P25	0.02	0.02	0.03	0.03
P50	0.04	0.05	0.07	0.07
P75	0.08	0.10	0.11	0.11
P90	0.15	0.15	0.17	0.16
P95	0.22	0.20	0.20	0.21
P99	0.37	0.38	0.34	0.31
Mean	0.06	0.07	0.08	0.08

Notes: The table splits the sample of sellers into quartiles of employment, and reports the distribution of the standard deviation of prices across buyer for each quarter. Q1 refers to sellers with less than 162 employees, Q2 includes sellers with [163,397] employees, Q3 includes sellers with [398,1021] employees, and Q4 includes sellers with more than 1026 employees.

Table A.3: Persistence in price gaps

	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$	$k=9$	$k=10$	$k=11$	$k=12$
β_k	0.832***	0.779***	0.744***	0.737***	0.717***	0.710***	0.682***	0.694***	0.682***	0.706***	0.704***	0.671***
	(0.0148)	(0.0143)	(0.0135)	(0.0169)	(0.0185)	(0.0174)	(0.0147)	(0.0148)	(0.0167)	(0.0183)	(0.0186)	(0.0202)
Within R2	0.678	0.610	0.564	0.537	0.516	0.507	0.468	0.467	0.444	0.437	0.416	0.390
Observations	1,708,884	1,692,594	1,686,877	1,464,196	1,471,887	1,388,135	1,481,891	1,474,561	1,436,200	1,172,285	981,214	983,564

Notes: The table reports the results of estimating equation (5) by OLS separately for $k = 1, ..., 12$. All columns include product-level fixed effects.

Table A.4: Summary statistics on network

Number of products	189,947
Number of firms	18,292
Possible product-buyer pairs	> 3 billion
Product-buyer pairs with positive sales	876,852
Sales of $i \in S$ / total sales	0.36
Intermediate sales of $i \in S$ / total sales	0.15
Intermediate sales of i with multiple buyers / total sales	0.08

Notes: The table summarized the network of products and firms used for our baseline counterfactual. $i \in S$ refers to products for which product codes are available.

B Data

B.1 Additional datasets

Here we outline additional datasets we use in the paper:

Form 22 (F22 or Income Declaration Form): This is a form submitted by firms to compute their annual tax payments, and therefore contains total sales in the year, intermediate inputs purchases, salaries, among other variables. We use this dataset for regressions where we measure buyer's size with their total sales, and for calibration of the model.

Affidavit 1887 (DJ1887): This an annual form submitted by firms, where they declare all their employees with either a full-time or a part-time job contract. For each firm, it contains what months each worker was employed, her net salaries and whether it was a full-time or a part-time job.

Affidavit 1879 (DJ1879): This an annual form submitted by firms, where they declare all their contracted or short-term workers. For each firm, it contains how many months each worker was employed, and how much it was retained for taxes and social security.

We use DJ1887 and DJ1879 for two purposes in the paper. First, our baseline sample uses firms (either as buyers or sellers) that have at least one paid worker in 2021. Second, for regressions that use a measure of employment at the firm level, we sum across all workers$\times$months in both forms and divide them by 12.

B.2 Data cleaning

We take the following steps to organize and clean the transaction data in EI:

i. We drop any transaction whose value is above 100 billion CLP (10^10), and price or quantity is non-negative.

ii. We discard invoices where the seller and buyer ID are the same

iii. We eliminate invoices that are cancelled or deemed invalid. For this, we use credit notes which give _new_ or _updated_ total amounts for each invoice. We drop documents where the new total amount differs by more than 1% with respect to the original total amount in the invoice

iv. We keep firms that in 2021 had at least one paid worker, and a valid F22.

v. Then, we define a product using the seller ID, the product code and the municipality for the seller declared in an invoice. Firms can report up to five codes, and whenever they declare the code is EAN we use it. Firms _write_ the municipality, thus it is open to typos. When we cannot identify a selling municipality, we define the product only using the seller ID and product code.

vi. To further refine our product definition, we only consider codes that fulfill the following: - Are at least 3 characters long - Have a number - For a given text description of the product, there is a unique product code - For a given product code, there is a unique text description of the product

vii. We eliminate transactions where the product's recorded price deviates from the average price recorded in other transactions from the same month by more than 1 log point.

C Model derivations

C.1 Equilibrium characterization

The cost of the input bundle for product i is given by

$$mc_i = \left[[1 - \bar{\alpha}_i]\, w^{1-\sigma} + \bar{\alpha}_i q_i^{1-\sigma} \right]^{\frac{1}{1-\sigma}}. \tag{C.1}$$

Here the cost of the fixed factors, and q_i is the cost of the intermediate input bundle:

$$q_i = \left[\sum_j \bar{\omega}_i^j \left[q_i^j \right]^{1-\eta} \right]^{\frac{1}{1-\eta}}, \tag{C.2}$$

with

$$q_i^j = \left[\sum_{i' \in j} \bar{\omega}_{i'i} p_{i'i}^{1-\rho} \right]^{\frac{1}{1-\rho}}. \tag{C.3}$$

The price of the final good is:

$$P = \left[\sum_j \gamma^j \left[P^j \right]^{1-\eta} \right]^{\frac{1}{1-\eta}}, \tag{C.4}$$

with

$$P^j = \left[\sum_{i \in j} \bar{\gamma}_i^j p_{ic}^{1-\rho} \right]^{\frac{1}{1-\rho}}. \tag{C.5}$$

Demands are given by:

$$x_{ii'} = \bar{\omega}_{i'i} \left[\frac{p_{ii'}}{q_{i'}^j} \right]^{-\rho} m_{i'}^j; \quad c_i = \bar{\gamma}_i \left[\frac{p_{ic}}{P^{j(i)}} \right]^{-\rho} C^{j(i)}. \tag{C.6}$$

with

$$m_i^j = \bar{\omega}_i^j \left[\frac{q_i^j}{q_i}\right]^{-\eta} m_i,$$
$$m_i = \bar{\alpha}_i \left[\frac{q_i}{mc_i}\right]^{-\sigma} b_i, \tag{C.7}$$

and

$$C^j = \bar{\gamma}^j \left[\frac{P^j}{P}\right]^{-\eta} C. \tag{C.8}$$

Demand for the fixed factor is

$$l_i = [1 - \bar{\alpha}_i] \left[\frac{w}{mc_i}\right]^{\sigma} y_i. \tag{C.9}$$

An equilibrium for this economy is given by product level prices, $\{p_{ii}\}$, $\{p_{ic}\}$, costs $\{mc_i, q_i\}$, $\left\{q_i^j\right\}$, quantities $\{c_i\}$, $\{y_i\}$ and inputs choices: $\{l_i\}$, $\{m_i\}$, $\left\{m_i^j\right\}$, and $\{x_{ii'}\}$, final prices $\{P^l\}$ P and bundles$\{C^j\}$, C and factor prices:. such that: $w = 1$ and the pricing equations (10), (C.1), (C.2), (C.3), (C.4), (C.5), the demands (C.6), (C.7), (C.8), (C.9), and market clearing (8), (9) are satisfied.

D Solution Algorithm

We now present the solution algorithm, the set of equations, and the notation for Matlab. We evaluate the response of the economy to a change in intermediate markups, $\hat{\mu}_{if}$, and assume that the change in markups to final consumers are the same for all products of the same firm $\hat{\mu}_{ic} = \hat{\mu}_{f(i)c}$,

i. **Step 1:** Solve for all price changes. We proceed in the following steps.

   (a) **Make a guess for the change in marginal cost of each firm:** $\widehat{mc}^*_f \equiv \widehat{mc}_f^{1-\rho}$. This is an $NF_T \times 1$ vector. We iterate on $\widehat{mc}_f^{1-\rho}$instead of $\widehat{mc}_f$ to speed up code.

   (b) **Define the firm to firm weighted markups:** $\hat{\mu}^*_{ff'} \equiv \sum_{j \in f} \theta_{jf'} \hat{\mu}_{jf'}^{1-\rho}$.

   (c) **Iterate the following system to find** $\widehat{mc}^*_f$

$$\hat{p}^*_{ff'} \equiv \hat{\mu}^*_{ff'} \times \widehat{mc}^*_f,$$

and

$$\hat{q}^{M*}_{f'} = \left[\sum_{f \in M} \hat{p}^*_{ff'} \right]^{\frac{1-\eta}{1-\rho}}; \hat{q}^{O*}_{f'} = \left[\sum_{f \in O} \hat{p}^*_{ff'} \right]^{\frac{1-\eta}{1-\rho}}.$$

and

$$\hat{q}^*_f = \nu^M_f \hat{q}^{M*}_f + \left[1 - \nu^M_f \right] \hat{q}^{O*}_f.$$

and

$$\widehat{mc}^*_f = \left[1 - \alpha_f + \alpha_f \hat{q}_f^{*\frac{1-\sigma}{1-\eta}} \right]^{\frac{1-\rho}{1-\sigma}}.$$

(d) Compute all prices

$$\widehat{mc}_f = \left[\widehat{mc}_f^*\right]^{\frac{1}{1-\rho}}$$
$$\hat{p}_{if'} = \hat{\mu}_{if'}\widehat{mc}_{f(i)}$$
$$\hat{p}_{ic} = \hat{\mu}_{f(i)c}\widehat{mc}_{f(i)}$$
$$\hat{q}^M_{f'} = \left[\hat{q}^{M*}_{f'}\right]^{\frac{1}{1-\eta}}$$
$$\hat{q}^O_{f'} = \left[\hat{q}^{O*}_{f'}\right]^{\frac{1}{1-\eta}}$$
$$\hat{q}_{f'} = \left[\hat{q}^*_{f'}\right]^{\frac{1}{1-\eta}}$$

$$\hat{P}^M = \left[\sum_{f\in M}\gamma_f \hat{p}_{fc}^{1-\rho}\right]^{\frac{1}{1-\rho}}$$
$$\hat{P}^O = \left[\sum_{f\in O}\gamma_f \hat{p}_{fc}^{1-\rho}\right]^{\frac{1}{1-\rho}}$$

and

$$\hat{P} = \left[\beta^M\left[\hat{P}^l\right]^{1-\eta} + \left[1-\beta^M\right]\left[\hat{P}^l\right]^{1-\eta}\right]^{\frac{1}{1-\eta}}.$$

ii. **Step 2:** Solve for changes in the total quantity of each product relative to the change in final consumption, $\frac{\hat{y}_i}{\hat{C}}$. We proceed in the following steps.

(a) **Compute change in relative final demand of each product:**

$$\frac{\hat{c}_i}{\hat{C}} = \left[\frac{\hat{p}_{ic}}{\hat{P}^{k(i)}}\right]^{-\rho}\left[\frac{\hat{P}^{k(i)}}{\hat{P}}\right]^{-\eta}.$$

(b) **For products that are only sold to final consumers, set**

$$\frac{\hat{y}_i}{\hat{C}} = \frac{\hat{c}_i}{\hat{C}}.$$

(c) **Then guess $\frac{\hat{y}_i}{\hat{C}}$ for products [$1 : NP_{XT}$], and compute**

$$\frac{\hat{b}_f}{\hat{C}} = \sum_{i\in f}\frac{b_i}{b_f}\frac{\hat{y}_i}{\hat{C}}.$$

and update the guess using

$$\frac{\hat{y}_i}{\hat{C}} = \widehat{FDEM}_i + \sum_f INTDEM_{if} \frac{\hat{b}_f}{\hat{C}}.$$

with $\widehat{FDEM}_i \equiv \frac{c_i}{y_i} \frac{\hat{c}_i}{\hat{C}}$, and $\boldsymbol{INTDEM_{if}} = \left[1 - \frac{c_i}{y_i}\right] \frac{x_{if}}{\sum_f x_{if}} \left[\frac{\hat{p}_{if}}{\hat{q}_f^{k(i)}}\right]^{-\rho} \left[\frac{q_f^{k(i)}}{\hat{q}_f}\right]^{-\eta} \left[\frac{\hat{q}_f}{\widehat{mc}_f}\right]^{-\sigma}$

(d) **From the labor market clearing, solve:**

$$\hat{C} = \left[\sum_i \left[\frac{1}{\widehat{mc}_f}\right]^{-\sigma} \frac{\hat{b}_f}{\hat{C}} \frac{l_f}{L}\right]^{-1}.$$

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