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"Consumer's knowledge and price discrimination: evidence from the Peruvian electricity market"

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Abstract

This research studies information and search cost asymmetry across consumers as a source of price discrimination by firms. Even though the theoretical framework on the topic is broad, empirical research is limited by market information availability. Due to this reason, most of the studies focus on price dispersion as a symptom of price discrimination rather than actual prices. The Peruvian non-regulated electricity market is characterized by business-to-business transactions, with high levels of transparency and data availability. Using contract-level information from the year 2018, the analysis reveals that clients with previous experience in the market obtained price discounts compared to unexperienced ones after controlling for relevant client, supplier, and contract characteristics. Moreover, unexperienced firms with larger revenues, a proxy to their organization size, were able to obtain lower prices than smaller firms after controlling for electricity demand. This study provides new evidence to the limited literature on the topic and a novel market setting where further research can be done.

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1. Introduction

In recent years the Peruvian electricity market has seen relevant changes in its competitive landscape. The unbalance between electricity demand and supply growth due to lower economic activity and the delay of relevant mining projects led to oversupply in the market. As a result, electric energy spot prices dropped to minimums and electricity suppliers had to intensify competition in a market growing below their expectations (Tamayo et al., 2020). Since distribution companies, which primarily supply regulated clients (households and small businesses), were already fully contracted in the long-term, competition shifted towards the non-regulated market. In this market, businesses directly engage in Power Purchase Agreements with electricity suppliers at bilaterally negotiated prices for energy and power.

As a result, the spread between regulated and non-regulated average prices increased from US$ 3 per megawatt-hour (MWh) in 2015 to US$ 18 per MWh in 2018. That is, non-regulated prices offered savings of around 36% for the purchase of energy, which accounts for more than 50% of a regulated industrial consumer electricity bill (Osinergmin, 2022). In this scenario, the migration to this market increased rapidly, and by 2021 the number of non-regulated clients had multiplied by 7.7 compared to 2015. Even though competition increased (Semana Economica, 2019), with suppliers growing from 27 in 2013 to 36 in 2018 (Osinergmin, 2021), and regulation led to homogenous supply conditions in this market, price dispersion was still evident. The average Gini coefficient of prices was 0.082 in 2018, which means that there was an expected difference of 16.4% in the prices of two random contracts signed that year.

According to economic theory, price dispersion is a sign of price discrimination in the market (Stole, 2003). In the most general case, this occurs when a monopolist deviates from a single pricing strategy to capture all the consumers' surplus by charging each consumer their reservation price. At an industry level, price discrimination is feasible when consumers have heterogeneous preferences that can be exploited by competing firms setting differentiated prices. When consumers also have access to heterogeneous information, firms can not only charge higher prices to those with a price-inelastic demand but also charge a price premium to uninformed consumers. Several theoretical models have been developed to understand the mechanisms and assumptions for price discrimination under information asymmetry (Salop & Stiglitz, 1977; Varian, 1980).

Empirical research on the sources of price discrimination found that in the housing market of China, for example, non-local buyers of houses paid a price premium over local buyers. This result can be explained by the latter having better information about the housing market conditions in their cities (Zhou et al., 2015; Li & Chau, 2019). Also, U.S. hospitals obtained price reductions in the procurement of medical equipment after they purchased market benchmarking data services, allowing them to obtain better information about the distribution of prices in the market (Grennan & Swanson, 2019).

Given the large inflow of unexperienced consumers into the Peruvian non-regulated electricity market, we hypothesize that electricity suppliers exploited the existence of uninformed consumers in the market. Charging them with price premiums over informed consumers to increase their profitability. This heterogeneity arises either because of a bias in the client's information about the price distribution in the market, or because of a lower capability to reduce the information asymmetry. In both cases, it implies having higher search costs compared to firms that had prior experience buying energy in the non-regulated market.

Using contract-level information available from Osinergmin, the regulatory entity of the industry in Peru, our empirical analysis shows that, after controlling for consumer's demand and supplier characteristics, firms that had previous experience in the non-regulated market obtained price discounts compared to unexperienced firms. Moreover, unexperienced firms that had a larger organization (measured by the size of revenues) were capable of obtaining a lower price than smaller-sized firms, even after controlling for the size of electricity demand. We argue that this is explained by a lower marginal cost of increasing search efforts for companies with already well-established procurement teams.

To our knowledge, there are no existing empirical studies that evaluate the effects of information heterogeneity across consumers in a business-to-business electricity market. Hence, this research complements the existing literature on the sources of price discrimination and provides a new setting for the empirical study of this topic. This is possible thanks to the high level of transparency of information about the non-regulated electricity market in Peru. Moreover, our results can also be related to the negotiations field, as they clearly support the conclusions of previous studies where information is a tool to increase bargaining power.

Also, our conclusions are relevant to the market context in Peru. The reduction of the minimum power demand to become a non-regulated client from 200 kilowatts to 50 kilowatts (kW) is being discussed by policymakers (PCR, 2020). It is estimated that the approval of this regulatory change would lead a new swath of companies to migrate to the non-regulated market (La Republica, 2020). Thus, the results from this research could provide useful insights into their strategy in the sourcing of energy.

This thesis is organized as follows. In the second chapter, we review the relevant theoretical and empirical literature about price discrimination and information heterogeneity as a source of that market phenomenon, price dispersion as a symptom of price discrimination, and we also provide an overview of the main characteristics of the Peruvian non-regulated market and non-regulated contracts. In the third chapter, we describe the proposed methodology for the empirical analysis, the data sources, and the rationale behind the selection of the variables of the econometric model. In the fourth chapter, we show the results of the empirical analysis and discuss their implications and how they relate to the existing literature. Finally, in the fifth chapter, we discuss the main conclusions of the research, the limitations of the analysis, propose future research in the topic, and discuss policy implications.

2. Related Literature

In this section, we will review the main theoretical and empirical literature related to the topics of price discrimination and the influence of consumer information heterogeneity in the price dispersion observed in several markets. Also, we will provide an overview of the Peruvian electricity market's functioning and how non-regulated contracts are settled. Finally, we will discuss the hypotheses to be tested in the empirical section of this thesis.

2.1. Theoretical background

A broadly accepted definition of price discrimination is that it occurs when a firm offers two goods at prices that have a ratio different from their marginal costs (Stigler, 1987). They do so to increase profits when compared to a uniform pricing strategy (Stole, 2003). In its most extreme case, perfect or first-degree price discrimination is the case where a firm can set a price at each consumer's marginal willingness to pay. When the firm is a monopolist, has perfect information, and price discrimination is possible (there is no arbitrage between consumers and doesn’t have regulatory constraints), it captures all consumer surplus, and an efficient outcome is achieved (Armstrong, 2005). There are also settings in oligopolistic markets where the marginal consumer purchases at marginal cost, leading to a social surplus maximization situation where consumers can retain part of their surplus (Stole, 2003).

Second-degree price discrimination or non-linear pricing occurs when firms have information about the distribution of preferences in the market and thus, know of the existence of consumer types but are unable to observe each buyer’s type (Weichenrieder, 2004). In this scenario, firms rely on the self-selection of consumers by establishing a menu of quantity-tariff or quality-tariff bundles that maximizes profit (Chao & Nahata, 2015; Stole, 2003). In a monopolistic market, offering quantity discounts raise revenues as they encourage consumption in all the spectrum of consumers (Spence, 1977).

Finally, third-degree price discrimination is the practice of using information about observable consumers' characteristics to segment the market and offer differentiated prices (Bergeman et al., 2022). In contrast with second-degree price discrimination, the consumer will pay a constant price no matter the quantity purchased. In the most common setting, a monopolist that serves two markets with a homogeneous good will charge a lower price to the market with the highest price sensitivity (Varian, 1992). This result holds in oligopolistic markets if the firms rank the groups' price elasticities in the same order, leading the industry to unambiguously set a lower price for highly price-sensitive consumers (Dastidar, 2006).

Rather than price elasticity, in this thesis, we are interested in the role of imperfect information in explaining price discrimination in a homogeneous good market. One of the most influential works on this topic is Salop (1977), which introduces the heterogeneity in information gathering costs of buyers (also defined as search costs) as an additional source of price discrimination to typical demand functions (price sensitivity). The notion is that the monopolist will use price dispersion as a tool to sort consumers between informed and uninformed, charging a higher price to agents with higher search costs. The difference between this model and non-linear pricing schemes is that the firm incurs costs to sustain the price dispersion. This is done through the creation of "noise" in price and quality (in this case, between stores), which leads customers to deviations between their prior knowledge of the price distribution and the actual price distribution.

Salop and Stiglitz (1977) developed a model for an industry-level equilibrium where customers only differ in their search costs. They show that price dispersion can be an equilibrium result, with prices distributed between the perfectly competitive and monopolistically competitive prices. One interesting outcome of the model is that average market prices have an inverse relationship with the share of informed customers, providing a positive externality to uninformed customers.

It is important to note that in both models, the price dispersion is spatial. That is, the firms contemporaneously offer the same homogenous good at different prices at different stores. Varian (1980) provides an alternative scenario where price dispersion is temporal, and firms rely on the usage of sales to price discriminate between informed and uninformed customers. The main insight of the model is that stores randomize prices but use extreme prices with higher probability, charging informed customers the minimum price to have a positive profit and the reservation price to uninformed customers. This is consistent with the frequent practice by stores of selling a good at a given price most of the time and then offering a 25% discount for a short period. Why not sell the goods at an intermediate price? Also, the model shows that the optimal decision for customers with an intrinsically high search cost is to remain uninformed.

More recently, Pennerstorfer et al. (2020) proposed a clearinghouse model that relates information, prices, and price dispersion. They focus on the relationship between the share of informed consumers and the degree of price dispersion, finding an inverse U-shaped relationship. When there are no informed consumers, all firms charge the monopoly price, and when all consumers are informed, firms sell at marginal cost. If the share of informed consumers is between these two extreme values, that is, when informed and uninformed consumers coexist, firms face the dilemma of charging a higher price to exploit uninformed consumers or charging a low price to attract informed ones. This tension leads to a mixed-strategy equilibrium and price dispersion.

A different approach to explain the existence of an equilibrium with price dispersion is proposed by Burdett and Judd (1983). In their model, there is no ex-ante heterogeneity across agents; that is, firms face the same costs, and consumers are identical and rational. However, consumers do not know which firm offers the lowest price and incur the cost of search requesting quotations to minimize the expected cost of purchasing a good. This can be done either through sequential or non-sequential search. In this last case, the consumer decides the number of quotations it will request, which is a decreasing function of the search cost. Dispersion is provoked by the belief of firms that they might encounter a consumer that knows only one price.

Finally, Hopkins and Seymour (2002) show that, when introducing seller and customer learning in a dynamic setting, stable equilibriums with price dispersion in the market occur only under certain conditions. Either average consumer information must be low, prices be close to the monopoly level, or the information flow to consumers be exogenous (noisy search). Thus, the authors propose that price dispersion can be better understood as a disequilibrium phenomenon, where there is a constant flow of new customers without experience.

2.2. Empirical background

Even though price discrimination has received considerable attention from economic theorists for decades, it has only recently become a topic for rigorous empirical research. This can be partially explained by the improvement in market data availability. Empirical studies have focused on the identification and measurement of price discrimination, the sources of price discrimination, and the effects of price discrimination on profits, consumer welfare, and efficiency (Verboven, 2008). In this review, we will focus on the second stream of research since information heterogeneity across consumers as a source of price discrimination is the focus of this research.

Some of the first empirical studies on price discrimination evaluated the influence of market structure on price dispersion. For example, Borenstein and Rose (1994) show that airline fares in the U.S. had varying degrees of price dispersion, with higher levels of dispersion being consistent with submarkets where a larger number of competitors offered routes. Goldberg and Verboven (2001) study the price dispersion in the European car market, finding that bias in the preferences of consumers towards domestic brands in manufacturing countries explained the existence of higher mark-ups of manufacturers in their local markets. This effect, however, was moderated by the level of competition in the market. Bizan and Greenstein (2004) find that in the market of internet service providers in the U.S., service package offerings are consistent with second-degree price discrimination, where mostly explained by the degree of market competition in comparison to demand and cost factors.

Works aimed at studying the effects of heterogeneity in consumers' search costs are also mostly focused on their relationship with price dispersion. For example, McDonald and Wren (2016), using information from the car insurance market in the United Kingdom, find that consumers with lower search intensity capability on the internet registered a higher dispersion in the quoted insurance premiums. The authors argue that this is evidence of the "digital divide" in online activities. Pennerstorfer et al. (2020) evaluate the hypothesis that information and price dispersion have an inverse U-shape relationship for the retail gasoline market in Austria. The authors propose that commuter consumers have a higher capacity to sample gasoline prices in their commuting route than non-commuters and show that areas in Austria with a share of commuters closer to the lower and upper bounds exhibited lower levels of price dispersion.

Studies that analyzed transaction level information are scarcer but were able to estimate specific effects in prices rather than only measures of price dispersion. Zhou et al. (2015)

studied the effect of buyer heterogeneity in the form of geographic location on the price settled for houses in the city of Chengdu, China. It is argued that non-local buyers would have an information disadvantage compared to locals and thus have higher search costs. They show that non-local buyers paid a price premium over local buyers after controlling for house characteristics through a hedonic price model. Li and Chau (2019) develop a similar study for the Hong Kong housing market; however, they also differentiate sellers between developers of new projects and second-hand sellers. The authors find evidence that non-local buyers tended to pay a price premium compared to locals but also had a higher propensity to purchase from recognized developers and pay a premium to reduce the information asymmetry and risk.

Finally, the empirical literature we have reviewed so far focused on consumer markets, where consumers screen the market prices and buy at the lowest price possible. In business-to-business markets, the purchase of goods and services can be made through a more structured process, where quotations are requested, and then a negotiation process can occur before the purchase is completed. This situation resembles the setting of the model proposed by Burdett and Judd (1983) and described earlier. Thus, in business-to-business markets, asymmetry of information and search costs can influence price outcomes through the bargaining power of the firm. This is shown by Grennan and Swanson (2019), who study how access to information leads to price reductions in a business-to-business setting. Using information from U.S. hospital purchases of medical equipment, the authors find that having access to market benchmarking data services led to savings in future purchases. This effect was stronger for high-quantity items and short-term contracts. According to the authors, this is consistent with time-constrained negotiations and contract stickiness, which are concepts related to the negotiations literature.

2.3. The Peruvian electricity market

In the following subchapters, we will describe the organization and main characteristics of the non-regulated electricity market in Peru. Overall, it exhibits the characteristics of an oligopolistic homogeneous good market where price dispersion is an apparent symptom of price discrimination by electricity suppliers.

2.3.1. The non-regulated electricity market in Peru

Until 1992 the Peruvian electricity sector was comprised of State-run companies that acted as vertically integrated entities supplying the north, central and south systems. By then, the electrification coefficient, which measures the share of households that are connected to the electricity public service, was only 56.8%, while many isolated systems still existed in cities around the country due to a lack of investment in the transmission grid (Osinergmin, 2016).

With the goal of improving the quality of service and promoting private investment in the industry, the Government started a process of reforms in the sector by issuing the Law

N° 25844 of 1992 ("Electrical Concessions Law" or ECL). This law established the vertical disintegration of the industry into generation, transmission, and distribution. Generation would be a free-entry competitive market, while the latter two segments are regulated monopolies licensed by the State. The economic principles of the price signals were also clearly set, with marginal-cost pricing for generation activities, cost-based regulation with a regulated rate of return for transmission, and efficient-company with a regulated rate of return for distribution (MINEM, 1992).

The ECL created an independent system operator (ISO) named "Committee for the Economic Operation of the System" (COES), which would be responsible for coordinating the operation of the system and the economic transactions between generators and demand (MINEM, 1992). As is the case in most modern electricity markets, in Peru, generation companies produce energy under the command of the ISO (Hogan, 1998; Pollitt, 2012). COES programs the dispatch of the power plants based on their merit order, with the lower variable cost plants producing first until the demand is supplied at the minimum possible cost (Osinergmin, 2016).

The electricity market was also divided into two main sub-markets. In the regulated market, customers with a demand of 2,500 kW or less are supplied by distribution companies at tariffs set by the Osinergmin[1], the regulating and supervising entity of the industry (MINEM, 1993). This market is traditionally composed of households, small retailers, and small manufacturers due to their lower energy consumption. They do not need to sign a contract with the distribution company, as it is their right to be supplied. Distribution companies engage in Power Purchase Agreements (PPA) with generation companies and pass the generation costs to their regulated customers through the regulated tariff. Since the year 2006, through Law

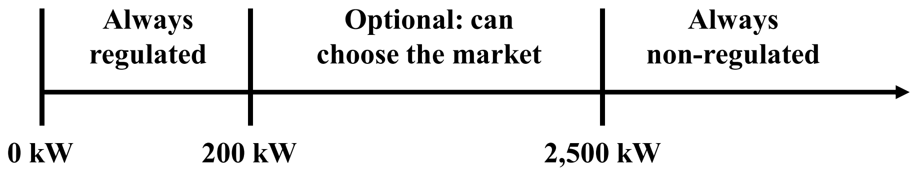
N° 28832, the supply of distribution companies with long-term PPA has been promoted by the Government with the objective of stabilizing the energy price paid by customers and supporting the construction of new power generation plants (Osinergmin, 2016).

Even though the non-regulated market was created by the ECL in 1992, it was not until 2009, after the issuing of the Supreme Decree N° 022-2009-EM, that it had a specific

[1] Organismo Supervisor de la Inversion en Energía y minería (Osinergmin).

regulation. The decree decreased the minimum demand set in the ECL to become a non-regulated client (also known as a "free" client) from 1,000 kW to 200 kW. Clients with demand between 200 kW and 2,500 kW are given the option to choose between being a regulated or non-regulated customer. Finally, clients with demand above 2,500 kW are mandatorily non-regulated (MINEM, 2009). Figure 1 summarizes the demand thresholds to participate in each market. Non-regulated customers are firms engaged in different economic activities, such as mining, manufacturing, infrastructure, retailing, and agriculture, among others (Osinergmin, 2016). They can engage directly in Power Purchase Agreements (PPA) with either generation or distribution companies and set a freely negotiated price for the supply of energy and power[2].

Figure 1: Energy markets and size of customers' power demand in Peru



Source: own elaboration.

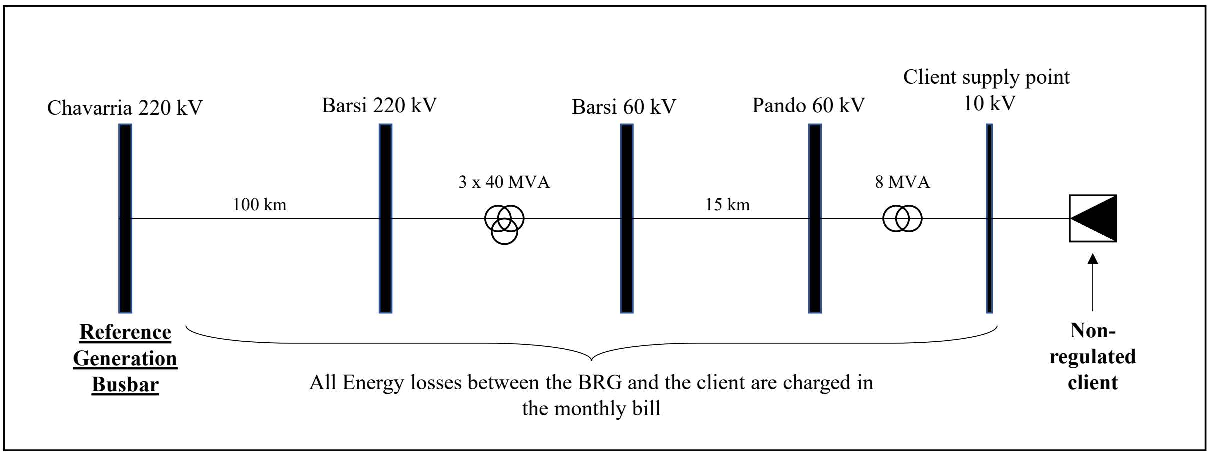
There are two other key issues set with the Supreme Decree N° 022-2009-EM. First, the users that will transfer from the regulated to the non-regulated market have to notify their distributor one year in advance. This is done once the client has signed a non-regulated PPA, which will usually consider the start of the supply twelve months after the signing. Second, prices must be settled at the Reference Generation Busbar (BRG for its acronym in Spanish). The BRG is the principal node of the main transmission system, which operates at a very high voltage (between 138 kV and 500 kV), that is closer to the customer and ensures the supply at the minimum cost (MINEM, 2009). Due to the interconnection of the northern, central, and southern systems into the SEIN in the year 2000 and the low levels of transmission restrictions across the system, these nodes are considered to have almost equal transmission loss rates. This allows prices set in the BRG to be comparable and thus provides more transparency to market participants.

Figure 2 shows an example of a single-line diagram for the supply of a non-regulated client. Any transmission losses between the BRG (Chavarria 220 kV substation) and the client are not the responsibility of the supplier and are charged as an extra cost to the client. Due to

[2] The total electricity tariff of a non-regulated customer is composed of the price of energy and power, the transmission toll, the distribution tariff, and other minor regulated charges. Only the energy and power prices are settled in a non-regulated PPA, while the other components are regulated by Osinergmin (MINEM, 1992).

the relevant differences in the loss rates of the regional transmission sub-systems, which leads to distortions when comparing a medium voltage price between cities, pricing at the BRG allows for a cleaner comparison to market prices.

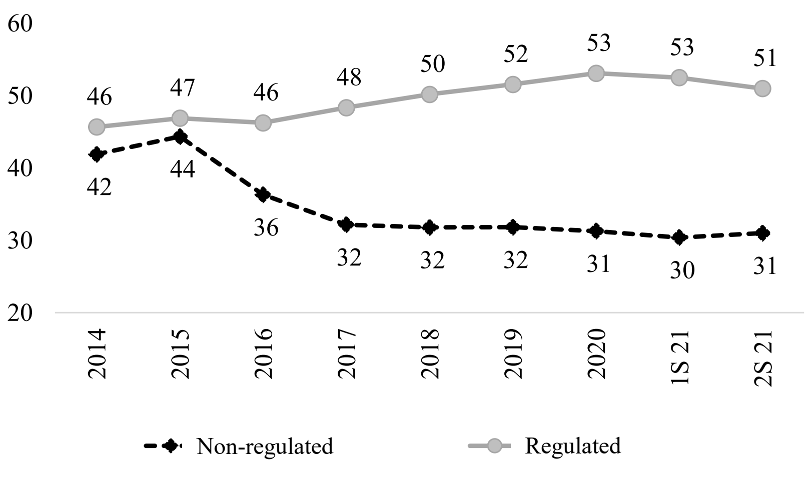
Figure 2: Example of the supply to a non-regulated client in medium voltage



Source: own elaboration.

The year 2016 marked the beginning of a prolonged period of oversupply of generation capacity in the Peruvian market. Lower energy demand growth rates coincided with the inauguration of several large-scale power plants which had started construction years before, leading to higher levels of competition among generation companies to secure PPA (Semana Economica, 2019; Tamayo et al., 2020). Since distribution companies had regulated market PPA signed for long-term supply, generators shifted competition towards the non-regulated market. Figure 3 shows how the spread in the average prices of these markets increased from US$ 3 in 2015 to US$ 10 in 2016 and US$ 18 in 2018.

Figure 3: Average energy price by market (US$/MWh)

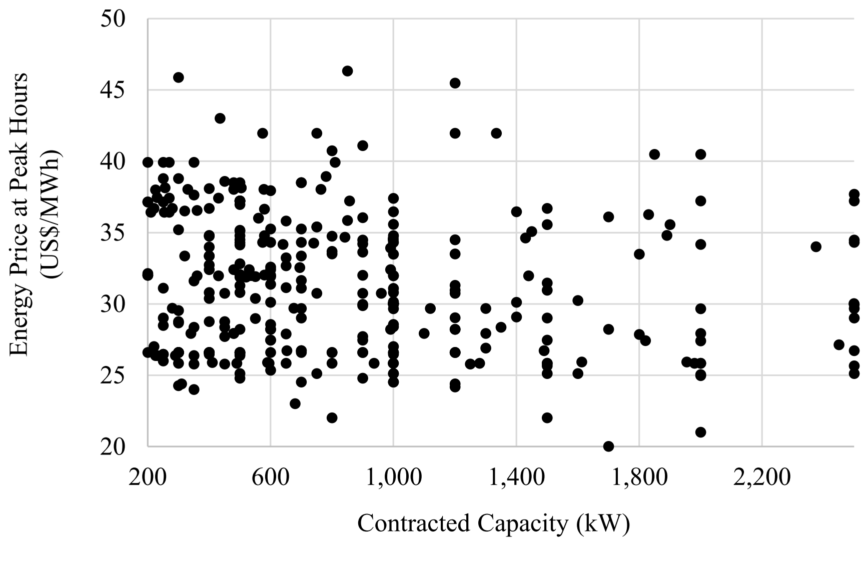


Source: Osinergmin.

In this context, a larger number of regulated clients decided to shift to the non-regulated market seeking savings in their electricity bills. Between December 2015 and October 2021, more than 2,200 customers converted from the regulated to the non-regulated market. This is around 97% of the total new non-regulated customers recorded by Osinergmin in that timeframe (Osinergmin, 2021). Figure 4 shows signed energy prices for the years 2017, 2018, and 2019 in the range of demand between 200 kW and 2,500 kW (optional clients). Even though a non-regulated electricity supply can be seen as a homogeneous good and competition was intense, the prices settled in this period show dispersion around the US$ 32 per MWh market average. However, there are no clear signs of second-degree price discrimination in benefit of larger customers in this range of demand.

The Gini coefficient is a useful measure of price dispersion used broadly in the reviewed literature. In 2018, the coefficient of prices in the non-regulated electricity market was 0.082, which means that there was an expected difference of 16.4% in the prices of two random contracts in the sample. The Gini coefficient ranged from 0.029 to 0.105 across the 12 economic groups that supplied the market. On average, these are smaller than the coefficients found by Borenstein and Rose (1994) for the U.S. airline market, which ranged from 0.018 to 0.416.

Figure 4: Contracted Energy Prices of Optional Customers by size of contract (2017-2019).



Source: Osinergmin.

2.3.2. Non-regulated contracts

In Peru, the non-regulated electricity contracts are publicly available from the regulator's webpage[3]. Although the frequency is not regular, contracts are uploaded with only some months of delay. This allows for an updated view of the terms and prices settled to any market participant. In this sense, the market has high levels of transparency. In the following lines, we will describe the main components of a PPA and the common practice in the settlement of terms based on our own review.

First, the contract states the legal name of the supplier, the client, and its economic activity. The location to be supplied is clearly identified in terms of address, supply point name, the voltage of the supply, and the nearest BRG. In some cases, clients negotiate the terms and prices for a bundle of locations at the same time. A single contract can include all of them, or separate contracts could be signed for each. The only requisite is that each location should have a contracted power of at least 200 kW (the minimum for non-regulated contracts).

Second, the contracted power is stated in kilowatts or megawatts (MW) per location. In case the client typically reduces power consumption in peak hours to reduce their electricity costs.[4] (peak shaving), a differentiated amount of power could be settled for peak and off-peak hours. A yearly scalable contracted power can also be seen in contracts related to operations that are expected to ramp up production over time. A billing methodology is set, where it is stated what value of power will be billed every month: peak power of the month, power coincident with the peak of the system, among other measures; and if a take-or-pay quantity will be set. Also, a penalty for consumption over the contracted power is usually included.

Third, the start date is defined, as well as the term of the contract in years. Information from contracts signed in the year 2018 shows that 9.4% of them had a term of at most two years, 51% at most three years, and 91% at most five years. This is significantly shorter than the existing PPA between generation companies and distributors to supply the regulated market, which has durations between 10 and 15 years. Only larger consumers, such as mines or large industries with demands over 50 MW, sign contracts with an equivalent length (Osinergmin, 2021).

Fourth, the initial prices are set for both power and energy at the BRG. In the case of power, generators usually charge the regulated power price, which is an accepted reference by market players as it is also the rate used to value power transfers in the spot market. It is usually

[3] https://www.osinergmin.gob.pe/empresas/electricidad/generacion/contratos-de-usuarios-libres
[4] Transmission and distribution tariffs are billed based on peak-hour power consumption (Osinergmin, 2016).

set at US$ per kW-month. For energy prices, more variability can occur, as this is the focal point of negotiation between generators and consumers. Due to the stabilization of spot prices in the oversupply period, generators started setting a flat price instead of charging a premium for consumption in peak hours. Energy prices are usually set at US$ per MWh. In the year 2018, signing a PPA at the average non-regulated market energy price meant a 36% saving for the client, whilst no significant savings could be obtained through the power price. We have not identified contracts where a take-or-pay quantity was set for energy billed; however, we acknowledge that it could happen in a few cases.

Fifth, a price indexation formula is set for power and energy prices. The formula aims to keep the monthly prices updated to fluctuations in the price of inputs for the supplier. Power prices are mostly indexed to the U.S. Producers Price Index (PPI) or to the regulated power price set by Osinergmin. In the case of energy, generators predominantly use the local natural gas price and, in the case of owning hydro or renewable generation, also the U.S. PPI. In case the price was set in Peruvian soles, the indexation formula will also include the exchange rate. Overall, price indexation formulas are very similar across generators. In case the supplier is a distributor, it will pass through the indexation formulas set in their own contracts with generation companies to the client.

Finally, there are some standard terms included in every contract. For example, the supplier must mandatorily comply with the Technical Norm of Electrical Service Quality (NTCSE) which sets the minimum quality standards of the service and the penalties in case of failure to comply with said standard. Also, a penalty for unilateral termination of the contract by the client is set. This is usually based on the expected loss of profit by the supplier. A process for solving any disputes during the term of the contract is also established.

2.4. Hypotheses formulation

The relevant growth in the number of consumers in the Peruvian non-regulated electricity market was explained by the larger savings offered for the purchase of energy and the growing competition by electricity suppliers amid an oversupplied generation market. Even though the electricity supply settled in non-regulated PPA can be seen as a homogeneous good, price dispersion is still observed in the market, a symptom of price discrimination. Based on the existing literature and the market characteristics, which could be the source of heterogeneity exploited by electricity suppliers?

Typical non-linear pricing (or second-degree pricing discrimination) occurs when firms know about the existence of heterogeneity in the market but not the specific characteristics of each consumer (Weichenrieder, 2004). These types of situations can be found in retail markets, where there is an abundant number of consumers, and it's only feasible for firms to establish pre-defined bundles for consumers' auto selection or incentivize a larger consumption of the good through price discounts (Spence, 1977).

In the case of the non-regulated electricity market, where suppliers engage with a reduced number of firms seeking a PPA, the identification of characteristics of the consumers is feasible on a cost-effectiveness basis, allowing for case-by-case discrimination. Non-regulated consumers sign their PPA for the total of their installed capacity of electricity consumption, revealing to the supplier their maximum potential demand. However, electricity demand is relatively price-inelastic for firms that use it as an input of production; thus, price discounts would not be effective in incentivizing a larger consumption. Rather, suppliers would view bigger consumers as more attractive due to their overall energy consumption potential and be willing to aggressively compete to secure the contract. It could also be argued that bigger clients would have larger potential savings from obtaining discounts and be more willing to increase their search efforts. Thus, our first hypothesis is the following:

Hypothesis 1: for non-regulated electricity contracts, the size of a client's demand has a negative relation to the contracted price.

When consumers differ in their search costs due to heterogeneity in information regarding prices, firms can exploit this situation by charging a premium to less informed consumers (Salop, 1977; Salop & Stiglitz, 1977; Varian, 1980). There is empirical evidence that this occurs in the housing market (Zhou et al., 2015; Li & Chau, 2019), fuel retailing (Pennerstorfer et al., 2020), car insurance (McDonald & Wren, 2016), and medical equipment supply (Grennan & Swanson, 2019).

The increase in the number of new non-regulated electricity consumers in the past years in Peru was mostly explained by the migration of regulated users (Osinergmin, 2021). This led to an increase in unexperienced consumers, which added to new firms in the market that were "born" non-regulated due to their demand size. Both of these groups of clients would have higher search costs compared to experienced firms in the market. There are two reasons why we expect unexperienced users to have higher search costs. First, although there exists public information about the identity of non-regulated clients, that is not the case for regulated clients, as they are only known by the exclusive distribution company of their area. These consumers decide to switch to a non-regulated supply either because of their own initiative (due to having information about the saving opportunities) or because they were identified and approached by a supplier. In the latter case, suppliers screen the market, searching for optional clients that had not switched to non-regulated yet, potentially entering into a bilateral negotiation without any competition. Second, unexperienced clients probably have a higher deviation in their prior about market prices and actual prices. For example, they might not know about the availability of public information about contracts or have an anchoring bias taking into reference the regulated prices. In summary, we argue that users who lacked the experience of signing a PPA had information disadvantages regarding the market prices when compared to more experienced non-regulated clients and that electricity suppliers could have exploited this information heterogeneity through third-degree price discrimination. Thus, our second hypothesis is:

Hypothesis 2: for non-regulated electricity contracts, clients that have previous experience in the market obtain a price discount compared to unexperienced clients.

Grennan and Swanson (2019) show that decreasing the information asymmetry resulted in savings for U.S. hospitals when purchasing medical equipment. In the case analyzed, hospitals purchased benchmarking data services to increase their accessibility to information. However, other options include increasing the sample of suppliers screened (Burdett & Judd, 1983), implementing stronger and more competitive procurement processes (Domberger et al., 1995), and requesting managerial and technical support from a parent company or hiring consultancy services (Mosonyi et al., 2019). Any of these efforts imply that the expected savings are greater than the search marginal cost. Firms with a larger organizational size (measured by revenue, for example) have relatively lower search marginal costs as they are more likely to have well-established procurement practices, with specialized offices and experienced buyers (Kaufman, 2002; Barilla et al., 2015). Thus, we propose the following third hypothesis:

Hypothesis 3: for clients that sign a non-regulated electricity contract for the first time, having a larger size in terms of revenues leads to price discounts compared to smaller clients.

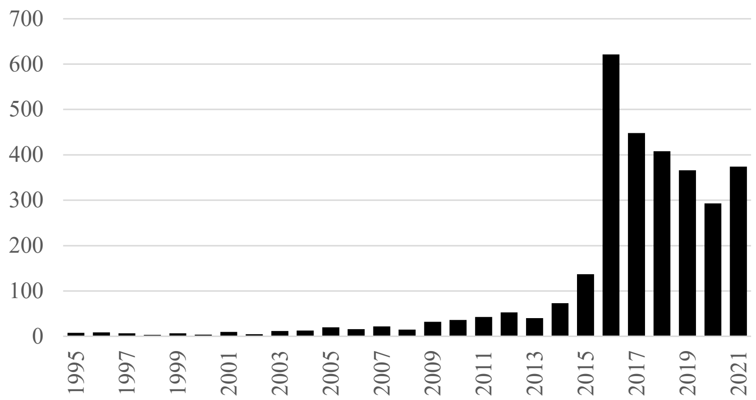
3. Data and Method

In this section, we will describe the dataset and methodology used to empirically test the proposed hypotheses.

3.1. Dataset

The main source of information for the empirical analysis is the public database of non-regulated electricity contracts available on Osinergmin's website. This database includes the universe of more than three thousand signed non-regulated contracts in the period 1995 to 2021 and provides a downloadable scanned version of each contract. Figure 5 shows the number of contracts signed by year and the steep increase registered since 2016. The regulatory agency publishes the "Monthly Non-regulated Electricity Market Report", which processes the information from the contracts into a report that includes variables such as the contracted power, start date, term, and prices, among other characteristics of the contract.

Figure 5: number of non-regulated electricity supply contracts signed by year in Peru



Source: Osinergmin

During the review of the database, we identified that the processed information included in the report contained several errors when compared to the original contracts. These include duplicated registry of contracts, as well as errors in the legal name of the client, date of signing, and base prices of energy, among other characteristics. To overcome this issue, we reviewed every single contract to verify the variables of interest and clean the database. As this is a time-intensive task, we selected one year to develop this detailed review and construct a database that would contain verified values for our empirical analysis.

We selected the year 2018 for our analysis due to two main reasons. First, since the number of non-regulated contracts signed before 2016 is scarce, by the years 2016 and 2017, few companies had prior experience in the market. During the year 2018, experienced firms explained around 25% of the signed contracts, allowing for more observations and variability to test the hypotheses. Second, before 2018 there was still uncertainty about the extent of the oversupply in the market; thus, higher variability in medium-term price views was observed, and more difficult for clients to know the price distribution. By the year 2018, spot prices significantly stabilized, while influential forecasts made by the regulatory agency and the ISO showed that the oversupply would continue for the next years (Osinergmin, 2017; COES, 2017). Thus, contracts signed during that year would be less affected by discrepancies in market views across suppliers and clients.

After the amendment of material errors found in Osinergmin's database, we also implemented two relevant adjustments to our final contracts database. First, we excluded all addendum contracts to avoid cases where suppliers offered a price discount to clients that had the risk of migrating to a new supplier. Second, we collapsed into one observation separated contracts signed by a client with the same supplier, at the same date, and at the same prices. This means that a negotiation process between a client and a supplier for many locations that were separated into different contracts was only counted once. In this way, we avoid the artificial inflation of the observations. The mentioned amendments and adjustments reduced the universe of contracts in 2018 from 408 according to the original dataset to 361 in our reviewed dataset.

On the other hand, since in Peru only 273 firms were listed on the Lima Stock Exchange and had public financial information during 2018 (BVL, 2019), to obtain client-level information, we used the Top Publications' "Peru Top 10,000" report. This annual report includes marketing contact information about the ten thousand largest companies in the country in terms of revenue. The publisher states that for unlisted companies, sales and assets information is estimated based on tax reports. Since we couldn't verify the methodology, we limited the use of this database to only specific variables, matching them to the contracts database through the Unique Taxpayer Registry number (RUC). Supplier-level information was obtained from COES' "Annual Statistical Report" and Osinergmin's annual database of the "System of Commercial Information – SICOM". Both publications provide information about electricity supplier's sales, market share, assets, and technical characteristics of power plants, among other variables.

3.2. Dependent variable

Our main dependent variable is the base average energy price settled in each contract, which is measured in US$ per MWh. In case a differentiated price was established for peak and off-peak hours, we calculated a weighted average based on the energy consumption in each period during the first twelve months since the client appeared in Osinergmin's "Monthly Non-regulated Electricity Market Report". We assume that the client had a similar consumption pattern before and after signing the non-regulated contract. Following other studies where the price is the dependent variable, such as Zhou et al. (2015) and Adbi et al. (2021), we transform the average prices into their natural logarithms. We will use only the energy price because the power price is usually set at or around the regulated power price; thus it is not a relevant focus of negotiation and potential price discrimination.

3.3. Explanatory variables

For the test of hypothesis 1, our explanatory variable is the customer's demand size stated in the contract in terms of MW. Typically, suppliers tend to offer discounts on quantity purchases to induce consumption (Spence, 1977; Stole, 2003) or see bigger clients as more attractive and more willing to compete to secure a contract. Thus, we expect this variable to have a negative and statistically significant coefficient.

For the test of hypothesis 2, our main explanatory variable is the experience of the client in the non-regulated electricity market prior to the signing of the contract. For this, we created a dummy variable that takes value 1 if the customer had signed a non-regulated contract in a period before the year 2018. Clients with prior experience in the market were most likely to obtain knowledge about the market conditions, exposition to more suppliers, and less information disadvantage when negotiating their contracts (Hopkins & Seymour, 2002; Zhou et al., 2015). Our source is Osinergmin's historical database of contracts. We expect this variable to have a negative and statistically significant coefficient, indicating that experienced clients obtained price discounts compared to unexperienced ones. For a robustness check, we will use the count of the contracts signed by the client prior to the year 2018 as an alternative measure of experience.

For the test of hypothesis 3, our third explanatory variable will be the classification of the client as a large corporation. As a proxy of this classification, we use the "Peru Top 10,000" database to create a categorical variable with three tiers. In the first tier, we include companies that did not appear in the Top 10,000 ranking; in the second tier, we include companies that appeared in the ranking but were not part of the Top 1,000; and in the third tier, we include the 1,000 largest firms of the ranking in terms of revenue. Larger corporations have well-established procurement offices for the sourcing of different goods and services. This provides the client with procurement processes that comply with best-practice procedures and with experienced buyers (Kaufman, 2002; Mosonyi et al., 2019). We also argue that the marginal and relative cost of procurement processes should be smaller for large corporations, allowing for sufficient efforts to improve the market screening and competition even if the energy demand is small. We expect this variable to have a negative and statistically significant coefficient at the highest tier of revenues.

3.4. Control variables

Our control variables include client, supplier, and contract characteristics that can explain the price settled in a non-regulated electricity contract. In the case of client characteristics, we control for the client's size in terms of revenue by including a dummy that takes value 1 if the client is part of the top ten thousand companies in Peru. Larger companies should be able to sustain higher search costs for their procurement of goods and services while also being more attractive to suppliers due to a perceived lower risk of default (Vandana & Kaur, 2019). We also include a dummy that takes value 1 if the client operates in the agricultural or fishing industries. These industries have a higher demand risk due to their seasonal nature and exposure to weather shocks such as El Nino Phenomenon (SENAMHI, 2014). Thus, we expect agricultural and fishing companies to obtain price premiums compared to other industries. To control for the optionality of the client to be supplied in the regulated or non-regulated market, we include a dummy variable that takes value 1 if the client has a demand of up to 2.5 MW. Since the outside option of these clients is the regulated price, which is higher than the non-regulated, we expect optional clients to obtain a price premium compared to non-optional clients. Finally, we include a dummy that takes value 1 if the location of the supply is outside the region of Lima, the capital of the country.

Regarding supplier characteristics, we include a dummy that takes value 1 if the supplier is a generation company. Generators can directly sell the energy they produce to non-regulated clients whilst also being able to access the spot market to purchase energy and arbiter if needed. In comparison, distribution and commercialization companies can only resell at a mark-up the energy they buy from generators (MINEM, 1992), thus reducing their competitiveness due to the existence of a double margin in their prices to clients. We also included a dummy that takes value 1 if the supplier owns both renewable and thermoelectric generation assets. Generators that have a diversified portfolio of generation can reduce production volatility risk and their average cost of production, improving competitiveness over single-technology generators (COES, 2019). To control for suppliers' market power, we include the natural logarithm of the monetary sales in the non-regulated market in the year 2017. Finally, to capture unobserved characteristics of the suppliers that could influence contract prices, we also include supplier fixed effects.

A relevant contract-level variable for explaining the price is the duration of the contract. Longer contracts entail higher risks for the supplier due to the uncertainty over future market prices and costs. Thus, longer-term contracts would entail a price premium over shorter contracts. This implies a certain degree of endogeneity between the price and length of the contract. We propose two strategies to cope with this issue. First, we created a dummy variable that takes value 1 if the contract has a length of up to 3 years. Osinergmin and COES forecasts showed that the oversupply was expected to last until the years 2022-2023; thus, the market consensus would also be that prices were to remain stable over that period. We believe this assumption is valid considering the evidence shown in Figure 3. Non-regulated market prices were stable until 2021 at an average of US$ 31 per MWh, similar to that in 2018.

As a second strategy, we develop a robustness check using a Seemingly Unrelated Regression (SUR), where both the price and length of the contract are considered endogenous variables in two models that are simultaneously estimated (Zellner, 1962). Both variables are related through the error terms instead of explicitly including one of them as an explanatory variable. We expect the correlation of the error terms to be positive since longer contracts would increase the supplier's risk of a rise in energy prices leading to a risk premium in price. Finally, we will also include month fixed effects to control for unobserved time-related factors that might have influenced prices.

3.4. Descriptive statistics

In this sub-section, we will present the main descriptive statistics of the variables used in the empirical analysis. Table 1 presents a summary of the dependent, explanatory, and control variables included in the models and a brief description of them.

Table 1: Variables used in the empirical analysis

Name	Description	Type
ppa_avgprice	Average energy price, in US$/MWh	Dependent variable
lnprice	Natural logarithm of the average energy price	Dependent variable
length	Duration of the PPA, in n° of months	Robustness check dep. variable
ppamw	Power contracted, in MW	Explanatory variable
exp	1 if the client signed a PPA in the previous 10 years	Explanatory variable
logexp	Natural logarithm of the N° of PPA signed by the client	Robustness check exp. variable
firmsize	Categorical variable for client's revenue	Explanatory variable
top10k	1 if the client is part of the Top 10,000	Client control variable
seasonal	1 if the industry is agriculture or fishing	Client control variable
optional	1 if the client has a demand of up to 2.5 MW	Client control variable
province	1 if the client is located outside of Lima	Client control variable
gen	1 if the supplier is a generator	Supplier control variable
diversified	1 if the supplier owns a diversified generation matrix	Supplier control variable
lnsuppsales	Natural logarithm of the supplier's sales in 2017	Supplier control variable
shortppa	1 if contract length is 3 years or less	Contract control variable
month	Month of signing of the PPA	Time FE control var.
clusterid	Identification of the economic group of the supplier	Supplier FE control var.

Table 2 illustrates the summary statistics of the variables used in the empirical analysis. The mean value of the average price settled in the non-regulated contracts of our database is

US$ 31.7 per MWh, with a minimum of US$ 19 and a maximum of US$ 53. As a dependent variable we will use the natural logarithm of the price. The average length of contracts was 43 months, and 51% of contracts had lengths of at most 3 years. The average size of the contracts was 1.86 MW, with a minimum of 0.2 MW (or 200 kW), consistent with the existing regulation. Finally, 25% of the contracts were signed by experienced clients, 23% by firms that operate in seasonal economic activities, and 92% by optional clients.

Table 2: Variables used in the empirical analysis

	N	Mean	Std. Dev.	variance	min	max
ppa avgprice	361	31.732	4.804	23.078	19	53
lnprice	361	3.446	0.153	.023	2.944	3.97
length	361	42.975	18.259	333.397	4	150
ppamw	361	1.86	9.631	92.75	.2	150
exp	361	.252	0.435	.189	0	1
logexp	361	.262	0.511	.261	0	2.708
top10k	361	.684	0.465	.217	0	1
seasonal	361	.23	0.421	.178	0	1
optional	361	.922	0.268	.072	0	1
province	361	.501	0.501	.251	0	1
gen	361	.205	0.404	.163	0	1
diversified	361	.078	0.268	.072	0	1
lnsuppsales	361	11.056	1.709	2.92	0	13.903
shortppa	361	.51	0.501	.251	0	1

Table 3 presents the pairwise Pearson's correlations between the variables included in the models. The natural logarithm of price shows statistically significant correlations with the experience (*exp*) and the client's size variable (*top10k*). That is not the case for *length* and the contracted MW (*ppamw*). However, the optional dummy variable has a positive and statistically correlation with price. The maximum pairwise correlation found between variables that are included in the same model is 0.57, between the dummies for generator (*gen*) and *diversified*. Moreover, the Variance Inflation Factor (VIF) estimated for the variables included in the regression models did not surpass the generally accepted threshold of 10. Thus, problems of high multicollinearity are unlikely in our empirical analysis.

Table 3: Pairwise Pearson's correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) lnprice	1.00												
(2) length	0.01	1.00											
(3) ppamw	-0.04	0.31***	1.00										
(4) exp	-0.34***	0.10*	0.20***	1.00									
(5) logexp	-0.30***	0.07	0.17***	0.89***	1.00								
(6) top10k	-0.18***	0.00	-0.03	0.31***	0.29***	1.00							
(7) seasonal	0.02	0.12**	-0.04	-0.01	-0.05	0.03	1.00						
(8) optional	0.24***	-0.23***	-0.41***	-0.31***	-0.31***	-0.04	-0.06	1.00					
(9) province	-0.07	0.13**	0.04	0.08	0.03	-0.09*	0.47***	-0.02	1.00				
(10) gen	-0.49***	0.13**	0.22***	0.29***	0.26***	0.14***	-0.13**	-0.34***	-0.12**	1.00			
(11) diversified	-0.34***	0.31***	0.29***	0.19***	0.11**	0.04	-0.06	-0.15***	0.06	0.57***	1.00		
(12) lnsuppsales	0.07	0.11**	0.15***	0.03	0.03	0.09*	-0.21***	-0.15***	-0.41***	0.10*	0.21***	1.00	
(13) shortppa	0.06	-0.68***	-0.08	-0.07	-0.09*	0.06	-0.20***	0.13**	-0.25***	0.00	-0.17***	0.06	1.00

**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

3.5. Method

Since our dataset is a cross-section of contracts signed in the year 2018, this study uses a log-linear Ordinary Least Squares (OLS) regression to test the hypotheses. A Breusch-Pagan test was first performed on a simplified version of the model, showing that the errors were heteroskedastic. Thus, we use a log-linear specification and robust standard errors to cope with heteroskedasticity issues in the regression. This approach follows previous studies on the subject, such as Zhou et al. (2015) and Li and Chau (2019), or on the topic of pricing analysis, such as Adbi et al (2022).

Equation 1 shows the formal notation of the baseline regression where only control variables are included. The dependent variable Pi is the average price of energy in US$ per MWh settled in contract i. The vector X_i includes control variables related to the characteristics of the client that signed the contract, vector Y_i variables related to characteristics of the contract, and vector Z_i variables related to characteristics of the supplier. Finally, δ_{month} is a vector of dummy variables that control for time fixed effects.

$$Ln(Pi) = \alpha_0 + \alpha_1 X_i + \alpha_2 Y_i + \alpha_3 Z_i + \delta_{month} + \varepsilon_i \quad (1)$$

To test hypothesis 1, we include the variable $PPAMW$, which measures the size of the contract in terms of MW. As shown in Equation 2, the coefficient of interest is β_1.

$$Ln(Pi) = \alpha_0 + \beta_1 PPAMW_i + \alpha_1 X_i + \alpha_2 Y_i + \alpha_3 Z_i + \delta_{month} + \varepsilon_i \quad (2)$$

To test hypothesis 2, we include the variable EXP, which is a dummy that takes value 1 if the client had previously signed a non-regulated contract. We initially exclude the variable $PPAMW$ from Equation 3 to estimate the independent effect of EXP through the coefficient β_2.

$$Ln(Pi) = \alpha_0 + \beta_2 EXP_i + \alpha_1 X_i + \alpha_2 Y_i + \alpha_3 Z_i + \delta_{month} + \varepsilon_i \quad (3)$$

In our main equation (4), we test the effects of $PPAMW$ and EXP and their interaction (coefficient β_3). Also, given the possibility that we are omitting a relevant variable that characterizes the suppliers, such as specific marketing strategies that target unexperienced consumers, we include θ which is a vector of dummy variables for each of the supplier's economic groups. Due to the existence of high levels of multicollinearity between the supplier fixed effects variable and the vector of supplier characteristics Z_i, we exclude the latter from the regression.

$$Ln(Pi) = \alpha_0 + \beta_1 PPAMW_i + \beta_2 EXP_i + \beta_3 PPAMW_i x EXP_i + \alpha_1 X_i + \alpha_2 Y_i + \delta_{month} + \theta_{supplier} + \varepsilon_i \qquad (4)$$

To test hypothesis 3, we estimate equation 5 for two sub-samples of contracts signed by experienced and unexperienced clients. Here, we include the categorical variable $FirmSize_i$, which classifies clients into three tiers of revenue. Since this model is estimated using sub-samples based on the experience of the firm, we exclude the variable EXP from this analysis. Time and supplier fixed effects are also included.

$$Ln(Pi) = \alpha_0 + \beta_1 PPAMW_i + \beta_4 FirmSize_i + \alpha_1 X_i + \alpha_2 Y_i + \delta_{month} + \theta_{supplier} + \varepsilon_i \qquad (5)$$

Finally, since there could be an issue of reverse causality when using the duration of the contract as a control variable to explain the price, we use a Seemingly Unrelated Regression (SUR) as a robustness check for our main results. Zellner (1962) proposed the SUR model as an alternative and more efficient method to estimate a set of regression equations when compared to equation-by-equation OLS. This model can be applied to cases where one or more of the explanatory variables in an equation is also a dependent variable in another equation or when none of the variables are simultaneously explanatory and dependent in nature, but there could be interactions in the independent equations through the error terms' distribution (Srivastava & Giles, 1987).

Thus, we are able to evaluate the relationship between price and length (in months) through the error terms $\varepsilon_{p,i}$ and $\varepsilon_{l,i}$, avoiding any potential endogeneity issue from the inclusion of the latter as an explanatory variable. We expect the errors to be positively correlated, as longer contracts would increase the price risk for the supplier. Equations 6 and 7, will be jointly estimated using the SUR regression. We exclude the control variable *shortppa* as it is directly related to the length of the contract, which is a dependent variable in this setting.

$$Ln(Pi) = \alpha_0 + \gamma_{p,1} PPAMW_i + \gamma_{p,2} EXP_i + \gamma_{p,3} PPAMW_i x EXP_i + \alpha_{p,1} X_i + \delta_{month} + \theta_{supplier} + \varepsilon_{p,i} \qquad (6)$$

$$Length_i = \alpha_0 + \gamma_{l,1} PPAMW_i + \gamma_{l,2} EXP_i + \gamma_{l,3} PPAMW_i x EXP_i + \alpha_{l,1} X_i + \delta_{month} + \theta_{supplier} + \varepsilon_{l,i} \qquad (7)$$

4. Results

In this section, we present and discuss the results of the empirical analysis to test the proposed hypotheses. We also present the robustness checks and limitations of the analysis.

4.1. Main results

Table 4 shows the results of the OLS estimation of equations 1, 2, 3 and 4 from the previous section. In the baseline regression that includes only control variables (1), we observe that the size of revenue (*top10k*) and being an *optional* client have a statistically significant effect on prices, with coefficients that have the expected sign. Also, being supplied by a generator (*gen*) had a negative statistically significant effect on prices, also consistent with our expectations. Signing a contract of 3 or fewer years (*shortppa*) of duration had no statistically significant effect on prices.

Table 4: OLS estimations to test hypotheses 1 and 2

	(1)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
ppamw		.002**	.002**			-.019	-.003
		(.001)	(.001)			(.013)	(.014)
exp				-.063***	-.048**	-.087***	-.058**
				(.021)	(.019)	(.023)	(.022)
exp_ppamw						.021	.006
						(.013)	(.014)
top10k	-.049***	-.047***	-.046***	-.032**	-.034**	-.026*	-.03**
	(.014)	(.014)	(.013)	(.015)	(.014)	(.014)	(.014)
seasonal	.014	.017	.017	.007	.009	.011	.013
	(.022)	(.022)	(.021)	(.022)	(.021)	(.022)	(.021)
province	-.023	-.027	-.03	-.015	-.021	-.017	-.024
	(.019)	(.019)	(.022)	(.019)	(.023)	(.019)	(.022)
optional	.066*	.096**	.078**	.041	.028	.052	.054
	(.038)	(.038)	(.034)	(.037)	(.034)	(.041)	(.036)
gen	-.146***	-.145***		-.133***		-.129***	
	(.029)	(.029)		(.027)		(.027)	
diversified	-.058	-.076**		-.056		-.072**	
	(.039)	(.036)		(.039)		(.035)	
lnsuppsales	.012**	.011**		.012**		.011**	
	(.005)	(.005)		(.005)		(.005)	
shortppa	.003	.004	-.014	0	-.016	-.001	-.016
	(.015)	(.015)	(.016)	(.015)	(.017)	(.015)	(.017)
Observations	361	361	361	361	361	361	361
R-squared	.321	.334	.483	.344	.48	.366	.499
Time FE	YES	YES	YES	YES	YES	YES	YES
Supplier FE	NO	NO	YES	NO	YES	NO	YES

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

When we add the variable *ppamw* (2a), which measures the size of the contract in terms of MW (client's demand), the related coefficient is positive and statistically significant at the 5% level. This result holds if we replace the supplier characteristics with a supplier fixed effects variable (2b). We perform a Wald's test for the *ppamw* coefficient estimated in both specifications and find that we reject the null hypothesis that the coefficient is zero at the 5% level in both cases. Thus, these results give no support to our first hypothesis, that consumers with greater demands were offered price discounts. According to equation 2b, an increase of 1 MW in a client's demand led to an increase of 0.24%[5] in price, ceteris paribus. The average size of contracts was 1.86 MW, and 87.5% of contracts had sizes below 2 MW; thus, the economic effect of this variable was negligible. Being an optional client led to a statistically significant increase of 8.1% in price compared to non-optional clients, ceteris paribus.

Equations 3a and 3b show the results of testing the effect of experience (*exp*). In both cases, we obtain negative statistically significant effects in price at the 1% and 5% level, respectively. The Wald's test also shows that we reject the null hypothesis that the coefficients are equal to zero at the 1% and 5% levels. For this variable, we obtain economically relevant results. Using equation 3b, contracts signed by experienced clients in the non-regulated market had a 4.7% price discount compared to contracts signed by unexperienced clients, ceteris paribus. It is important to note that *optional* loses statistical significance when including *exp* in the equation.

When we consider both explanatory variables and an interaction variable, the results show that the coefficients for *ppamw* and the interaction variable are not statistically significant. In both cases, the negative effect of *exp* is larger than in equations 3a and 3b, while remaining statistically significant. Experienced clients obtained an 8.3% price discount compared to unexperienced clients, ceteris paribus. The coefficient for optional clients is also not statistically significant in this model. It is important to note that including supplier fixed effects increased the goodness of fit in the models, as measured by the R-squared statistic. This means that there are unobserved supplier characteristics not included in the control variables. Overall, these results don't support hypothesis 1, but they do bring support to hypothesis 2.

To test hypothesis 3, we estimate a model where *ppamw* and *firmsize* are the explanatory variables, and experience is used to set two subsamples of contracts signed by unexperienced and experienced clients. Table 5 shows the result of the estimation. We can

[5] Since the model is log-linear, we estimate this value with the formula $(e^{\beta} - 1)x100$.

observe that for the unexperienced sub-sample (5a) there is a negative statistically significant coefficient for the second and third category of firm size. Being the effect larger for firms that belonged to the top 1,000. This result can be interpreted as follows, contracts signed by unexperienced firms that belonged to the top 1,000 companies in terms of revenue had prices 7.4% lower than contracts signed by unexperienced firms that were not part of the Top 10,000 Report (base category), ceteris paribus. The Wald's test shows that we reject the null hypothesis that this coefficient is equal to zero at the 1% level. In contrast, for contracts signed by experienced companies (5b), the coefficients of firm size are not statistically significant, and we can't reject the null hypothesis that they are equal to zero according to the Wald's test.

Thus, we find support for hypothesis 3, unexperienced firms that had bigger revenues obtained price discounts compared to smaller firms. In the case of experienced firms, it seems that having larger revenues, a proxy to organizational size and procurement capabilities did not provide any additional advantage in terms of price. This could imply that for these firms, experience in the market is the main resource they have for negotiating their contracts and overcoming their organizational size disadvantages.

Table 5: OLS estimations to test hypothesis 3

	(5a) Unexperienced	(5b) Experienced
ppamw	.008	.002**
	(.015)	(.001)
1bn.firmsize		
2.firmsize	-.022*	-.064
	(.013)	(.083)
3.firmsize	-.077***	-.056
	(.022)	(.082)
seasonal	-.006	.044
	(.021)	(.053)
province	-.019	-.046
	(.019)	(.07)
optional	.044	.086*
	(.072)	(.045)
shortppa	.008	-.03
	(.016)	(.051)
Observations	270	91
R-squared	.501	.631
Time FE	YES	YES
Supplier FE	YES	YES

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

4.2. Robustness check

For the robustness check of hypotheses 1 and 2 we first estimate a model where the dummy variable of experience is replaced by a count variable that measures the number of non-regulated contracts previously signed by the client. We transform this variable by adding one and then calculating the natural logarithm. Table 6 shows that the count measure of experience (*logexp*) is statistically significant in both specifications of the model. This result gives support to hypothesis 2. A 10% increase in the number of previously signed contracts led to a decrease of 0.4% in the price of the contract, ceteris paribus. In these model definitions, the size of the contract (*ppamw*) is still non-statistically significant. Thus, we also don't find support for hypothesis 1.

Table 6: Robustness check estimations to test hypotheses 1 and 2

	(4a rob.)	(4b rob.)
ppamw	.001	.001
	(.001)	(.001)
logexp	-.05**	-.045***
	(.02)	(.016)
logexpmw	.001	.002*
	(.001)	(.001)
top10k	-.032**	-.032**
	(.015)	(.014)
seasonal	.01	.012
	(.022)	(.021)
province	-.021	-.027
	(.019)	(.022)
optional	.075**	.06*
	(.037)	(.033)
gen	-.134***	
	(.027)	
diversified	-.081**	
	(.035)	
lnsuppsales	.011**	
	(.005)	
shortppa	-.002	-.02
	(.015)	(.017)
Observations	361	361
R-squared	.354	.498
Time FE	YES	YES
Supplier FE	NO	YES

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

A second approach for the robustness check is the estimation of a SUR regression where we jointly estimate two equations with the price and length of the contracts as dependent variables. The assumption is that both equations are correlated through their error terms, thus allowing for a more efficient estimation compared to an equation-by-equation approach. Table 7 shows that this method yields similar results to those presented previously. The experience variable is still statistically significant at the 1% level, while *ppamw* is non-significant. Overall, the estimated standard errors are slightly smaller than in the OLS regressions.

The results of the equation for length show that the coefficient of *optional* clients is negative and statistically significant. These clients signed contracts seven months shorter on average than non-optional clients, ceteris paribus. Some suppliers also obtained negative and statistically significant coefficients. These results imply that the length of the contract was more related to the supplier's strategy than to the client's preferences, supporting our previous argument about the possible exogenous definition of a contract's duration to the price negotiation. Moreover, the estimated correlation between error terms is positive, consistent with our expectations, and through the Breusch-Pagan test, we reject the null hypothesis that the correlation of the residuals of both models is equal to zero.

Table 7: Robustness check SUR estimation to test hypotheses 1 and 2

	(6) Price	(7) Length
ppamw	-.004	-1.655
	(.010)	(1.405)
exp	-.058***	-3.171
	(.019)	(2.551)
exp_ppamw	.006	2.051
	(.010)	(1.391)
top10k	-.030**	1.529
	(.014)	(1.863)
seasonal	.013	2.094
	(.016)	(2.215)
optional	.051*	-7.105*
	(.027)	(3.712)
province	-.025	-1.492
	(.018)	(2.476)
Observations	361	361
R-squared	.497	.360
Time FE	YES	YES
Supplier FE	YES	YES

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

4.3. Limitations and future research

A relevant limitation of this study is data availability. In the first place, our estimations are based on a verified dataset of contracts that cover only the year 2018 due to the need for time-intensive review and comparison between the databases processed by Osinergmin and the real contracts. Further efforts to improve data reliability in the databases over a longer time span could allow extensive research on the effects of the share of informed consumers and competition in price dispersion and the persistence in time of the price discrimination strategy we have identified in this study.

Also, the available information about contracts only shows the outcome of a negotiation process that we are not able to characterize, a limitation that forces us to make relevant assumptions. For instance, we assume that unexperienced consumers had a lower probability of having contact with more than one supplier when compared to experienced consumers. This is due to their non-public identity, while experienced consumers are easily identifiable to a supplier through Osinergmin's database of non-regulated contracts. Thus, the expected search cost of experienced consumers would be lower as they can be approached by many suppliers instead of them searching for the suppliers. Obtaining information about the negotiation process could allow for a deeper understanding of the impact that a client's strategy to reduce the information asymmetry could have on the price outcome, as found by Grennan and Swanson (2019) for U.S. hospitals. Examples of additional data include the implementation of a competitive process or bilateral negotiation, the number of quotations received by the client, the knowledge of the availability of public market information or the use of consultancy services. Thus, the sources of information disadvantage could be identifiable.

Moreover, there is a small number of firms in Peru that are publicly listed, which leads to limited information regarding the client's characteristics. We had to rely on the Top 10,000 ranking, which has no verifiable methodology to estimate revenues and other characteristics of non-public firms. The unreliability of this information led us to set only broad measures of firm size through dummy variables, which could be considered arbitrary.

Finally, there could be other unobserved firm characteristics that influenced the price. In the case of clients, for example, the credit rating of the firm, the characteristics of the board of directors and management, and the previous economic performance of the firm, among other variables. In the case of suppliers, we identified that the fixed effects increased the goodness of fit of the models; thus, unobservable variables outside of production factors could be relevant. These include commercial strategies that target specific market segments, risk adversity regarding exposition to longer contracts or specific economic sectors, and the level of spare capacity of the supplier, among others.

5. Conclusions and discussion

The empirical research shows that, in several markets, firms are able to implement price discrimination strategies to maximize their capture of the consumers' surplus. For this, firms exploit the heterogeneity in preferences and information availability across consumers. Studies that use transaction-level information to identify the sources of price discrimination are few, especially if we seek evidence from business-to-business markets. This research aimed to fill this gap by analyzing the case of the Peruvian non-regulated electricity market, which is an uncommon case of a highly transparent market. Our focus was on the effect of information and search costs heterogeneity across clients in the prices settled in contracts. Contract-level information for the year 2018 was compiled and used for the empirical analysis.

Summarizing our findings, we see that the demand size of the client did not lead to suppliers offering lower prices; instead, small price premiums were charged to larger clients. This is a result that is not in line with the theory of second-degree price discrimination and does not give support to our first hypothesis. When we include the experience variable and estimate the robustness checks, the demand size coefficient loses significance. This could be related to the minor frequency of large demand contracts in 2018. The inclusion of contracts from other years, where more heterogeneity in demand size is found, could lead to different results.

The experience variable, on the other hand, has a negative statistically significant coefficient that is consistent throughout the estimated models and robustness checks. Experienced clients obtained price discounts compared to unexperienced clients after controlling for client, supplier, and contract characteristics. This result is consistent with our second hypothesis and the reviewed theoretical framework, where firms price discriminates between informed and uninformed consumers, offering the former lower prices. It also adds to the findings of the empirical literature in the housing, insurance, and medical equipment markets, among others. To tackle a potential endogeneity issue between the price and length of the contract, we estimated a SUR model that sets both variables as dependent. The results show that the client's experience continued to be a relevant variable in explaining prices, whilst the length of the contract seems to be explained by factors related to the supplier's strategies.

To evaluate the influence of the client's procuring practices in mitigating the information disadvantage, we used the size of the firm in terms of revenues as a proxy of the organizational dimension and search cost absorption capabilities. Our results show that unexperienced firms that had larger revenues obtained price discounts compared to smaller-sized firms, in line with our third hypothesis. We argue that this is related to the existence of better and more competitive procurement processes within larger companies developed by experienced teams. In contrast, experienced firms in the non-regulated market did not obtain additional benefits from being larger when negotiating the price of their contracts. Hence, market experience allowed even small and less sophisticated firms to obtain similar prices to larger firms after controlling for other relevant factors.

As proposals in Peru for further liberalization of the non-regulated electricity market are frequent in recent years (PCR, 2020), it is expected that a swath of newcomers will enter the market, especially small and medium-size enterprises. These firms will face the challenge of negotiating their first PPA with a supplier. The findings of this research have several implications for firms and policymakers. Firms should set procurement processes that maximize competition and cost-effective strategies to overcome their information disadvantages. This recommendation applies to the general procurement practice of the firm, but especially when sourcing goods and services in new markets (as is the case of the non-regulated electricity market for formerly regulated clients).

In the case of the policymakers, Osinergmin should increase their awareness campaigns regarding the existence of useful public market information available to any potential new non-regulated client. Recently, with the sharp increase in fuel prices, Osinergmin started an aggressive marketing campaign to promote the use of the "Facilito" platform, which provides information about fuel prices in the thousands of gas stations supervised by the agency. A similar strategy could be followed for the Peruvian electricity market. Finally, other countries where wholesale or non-regulated electricity markets exist, such as Chile, should also evaluate the publication of detailed market information to provide consumers with better and more transparent price signals.

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