Information Frictions and Market Power: A Laboratory Study

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CESIFO WORKING PAPER NO. 6005
CATEGORY 11: INDUSTRIAL ORGANISATION
ORIGINAL VERSION: JULY 2016
THIS VERSION: APRIL 2020

ISSN 2364-1428

CESifo *Working Paper No. 6005*

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Abstract

In a laboratory experiment with supply function competition and private information about correlated costs we study whether cost interdependence leads to greater market power in relation to when costs are uncorrelated in the ways predicted by Bayesian supply function equilibrium. We find that with uncorrelated costs observed behavior is close to the theoretical benchmark. However, with interdependent costs and precise private signals, market power does not raise above the case of uncorrelated costs contrary to the theoretical prediction. This is consistent with subjects not being able to make inferences from the market price when costs are interdependent. We find that this effect is less severe when private signals are noisier.

JEL-Codes: C920, D430, L130.

Keywords: supply function competition, private information, wholesale electricity market.

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April 2020
We thank the editor and two annonymous referees for the excellent suggestions. We also thank José Apesteguia, Maria Bigoni, Colin Camerer, Enrique Fatas, Juan Imbett, Dan Levin, Cristina Lopez-Mayan, Margaret Meyer, Rosemarie Nagel, Theo Offerman, Stanley Reynolds, Albert Satorra, Arthur Schram, Jack Stecher and Chris Wallace for useful comments and discussions. Bayona acknowledges the financial support from Banc Sabadell, the Generalitat de Catalunya (AGAUR grant 2017 SGR 640), and the Spanish Ministry of Science, Innovation and Universities (Grant: PGC2018-098670). Brandts acknowledges financial support from the Spanish Ministry of Economy and Competitiveness (Grant: ECO2017-88130), the Severo Ochoa Program for Centers of Excellence in R&D (SEV2015-0563), and the Generalitat de Catalunya (Grant: 2017 SGR 1136). Vives acknowledges financial support from the Spanish Ministry of Economics and Competitiveness (Grant: ECO2015-63711-P), the Ministry of Science, Innovation and Universities PGC2018-096325-B-I00 (MCIU/AEI/FEDER, UE), and the Generalitat de Catalunya (AGAUR grants 2014 SGR 1496, and 2017 SGR 1244).

1 Introduction

We present the results of a laboratory experiment that examines the relationship between information frictions and market power in markets characterized by supply function competition. Information frictions have been found to be important in a number of markets with competition in schedules.[1] In our experimental markets, each seller has incomplete information about her own cost and others' costs and receives a private signal about own cost. On the basis of this information sellers compete in supply functions. Our experiment is fundamentally theory-based, but the setting is related to that of real-world markets characterized by competition in demand or supply schedules such as wholesale electricity markets, markets for pollution permits, or liquidity and Treasury auctions. Understanding what factors contribute to the existence of market power is a central issue and this is an area to which experimental economics can contribute. Specifically, in our laboratory study we can separately vary different elements of the information structure to study their causal impact on market power, something which is difficult with other types of empirical data.

Our design is based on Vives (2011), which structures a wide range of competitive environments where agents compete in schedules with private information, providing a tractable model. For example, the models of Klemperer and Meyer (1989) and Kyle (1989) can be seen as limit cases of Vives (2011). In this model, in the unique supply function equilibrium (hereafter, SFE), the interaction of cost correlation with noisy private information (hereafter, interdependent costs) generates market power that exceeds the full-information benchmark. When costs are interdependent, the SFE predicts a higher degree of market power than when costs are uncorrelated. The mechanism that explains these comparative statics results is the following. With interdependent costs, a Bayesian-rational seller must realize that a high price conveys the information that the average signal of her rivals is high, and therefore, the seller deduces that her own costs must also be high. Hence, she should compete less aggressively than if costs were uncorrelated in order to protect herself from adverse selection. As costs become more correlated the price is more prominent in the inference of costs, and equilibrium supply functions become steeper, leading to greater market power. In equilibrium, the combination of incomplete information and strategic behavior leads to greater market power when costs are interdependent than when they are uncorrelated. The SFE with uncorrelated costs coincides with the full-information equilibrium since sellers do not learn about costs from market prices.

Understanding whether high observed market power in natural markets is due to an equilibrium phenomenon or not is of policy importance. Indeed, a competition authority could

[1]The following papers argue for the importance of information frictions in markets with competition in schedules: wholesale electricity markets (Holmberg and Wolak 2016); liquidity auctions (Cassola et al. 2013); Treasury auctions (Keloharju et al. 2005); carbon dioxide emission permits (Lopomo et al. 2011). Holmberg and Wolak (2016) argue that cost uncertainty and information asymmetry are large in hydro-dominated markets.

mistakenly infer collusion from high margins in the wholesale electricity market when in fact generators were bidding non-cooperatively taking into account the information conveyed by the price. Or, similarly, the Treasury may suspect collusion in a bond auction when in fact bidders are responding optimally to the incomplete information environment they face. It is therefore crucial to test whether the theoretical predictions are borne out in the laboratory, or alternatively, whether we find deviations towards either more competitive or less competitive behavior than predicted by the equilibrium. Mitigating market power is a primary concern of regulators.[2]

The between-subjects experimental design is as follows.[3] Our two principal treatments differ in the correlation among costs holding everything else constant. The uncorrelated costs treatment is relevant in situations where cost shocks among sellers are purely idiosyncratic, while the positively correlated costs treatment is appropriate when cost shocks among sellers have a large systematic component due to events that commonly affect all sellers. In two supplementary treatments we also vary the variance of the noise in private signal in relation to the variance of costs. In each treatment, participants were randomly assigned to independent groups of twelve participants, each comprising four markets of three sellers. Sellers competed for several rounds, and within each group, we applied random matching between rounds in order to retain the theoretical model's one-shot nature. The buyer was simulated, and participants were assigned the role of sellers. Participants received a private signal about the uncertain cost and were then asked to submit a supply function. As in the theoretical model, and in contrast to most of the experimental literature, we used a normally distributed information structure that well approximates the distribution of values in naturally occurring environments. After all decisions had been made, the uniform market price was calculated and each subject received detailed feedback about her own performance, the market price, and the behavior and performance of rivals in the same market.

Although we simplified our design as much as possible, our experiment is somewhat complex. This is a reflection of the problem we are studying. In conducting our experimental test, we take received theory about competition in supply functions seriously, in the sense that it is important to relate the fundamental insights of theoretical market models to observed behavior. In this paper we study theoretical predictions in a laboratory environment. Naturally it would be of great interest to relate the theoretical model to field data, but we are not aware of any such data that would allow us to do this. Simpler designs may make it possible to study participants' decision processes more in detail. However, we think that the insights gained by studying simple designs alone are not enough. While simple experiments allow one to study a particular issue in detail, complex experiments are useful to obtain a more complete picture in environments where people face more than one problem at the same time. More complex games are certainly

[2] See, for example, Hortaçsu and Puller (2008) and Holmberg and Wolak (2016).

[3] In a between-subjects design participants are part of one treatment only.

required to understand situations of interest like market institutions.[4]

In our analysis we focus on the comparative statics of cost correlation. Expecting the data to be consistent with the point predictions may be too demanding in the context of complex environments like ours. Schotter (2015) discusses in detail the comparative-statics approach to using experiments for shedding light on theoretical models. Nevertheless, we also compare our data to point predictions for the SFE. Our findings are as follows. First, in our principal treatments average market power is not statistically significantly different between treatments with uncorrelated and interdependent costs. This is our central result. Second, consistent with the predictions of the SFE, we first find that average market power in markets with uncorrelated is close to what the SFE prescribes, while market power in the treatment with interdependent costs is far below the SFE prediction. This suggests that in treatments with interdependent costs participants are not sufficiently sophisticated with respect to the information structure and they do not make inferences from the market price.

We then analyze potential explanations of our results. We first ask whether alternative benchmarks to the SFE describe the data well. Market power in the SFE is the outcome of two separate factors characterizing fully rational behavior: strategic behavior with respect to the competitive environment and optimal processing of the information contained in the cost correlation, the signal structure and the particular signal received. By separately relaxing these two factors we find two alternative benchmarks to the SFE: price-taking behavior but informationally sophisticated (hereafter, PT); and behavior that is strategic with respect to the competitive environment but informationally naïve (hereafter, IN). In addition, we can also characterize behavior in the absence of both factors that correspond to full rationality (hereafter, PTIN). Notice that when costs are uncorrelated, the market price does not convey any information about costs and the SFE coincides with IN, while PT and PTIN are also identical. In the IN benchmark, participants do not extract information from the market price and this is equivalent to ignoring the correlation among costs. This corresponds to the fully cursed equilibrium concept of Eyster and Rabin (2005).

We study behavior in relation to the SFE and the three additional benchmarks, both for average behavior and, using a mixture model, for individual behavior. For the treatment with uncorrelated costs, we find that average behavior can reject the PT benchmark, but cannot reject the SFE benchmark. The results of our mixture model show that a very large percentage of subjects behave in accordance with the SFE. For the treatment with interdependent costs, our results show the IN is the only benchmark that cannot be rejected to explain average behavior. The mixture model results show that together the IN and PT benchmarks can explain most of the individual behavior. We also investigate whether our main result could be due to a bias related to Bayesian updating and find that this is not the case.

[4] See Kwasnica and Sherstyuk (2013) for a survey of experimental work on complex multi-unit auctions.

In the supplementary treatments, we find that if the signal is noisier in relation to the variance of costs compared to the principal treatments then interdependent costs lead to a statistically significant increase in average market power in relation to when costs are uncorrelated, but it is small in terms of size. Hence, with respect to our focus on average market power the results from the supplementary treatments mostly confirm those of the principal treatments. However, the inference problem of extracting information from the market price is less severe when signals are less precise since perhaps participants focus less on their private signals and more on the market price.

The rest of our paper is organized as follows. The literature review is in Section 2. In Section 3 we present the theoretical model and the hypotheses. Section 4 describes the experimental design and procedures. In Section 5 we present the experimental results, and in Section 6 we provide possible explanations of our results. We conclude in Section 7. Further details of the analysis are provided in Online Appendices.

2 Literature review

Some but few laboratory experiments have sought to analyze, as we do, competition in supply functions. Exceptions include the work of Bolle et al. (2013), who focus on testing predictions of the supply function equilibrium concept, as well as Brandts et al. (2008), and Brandts et al. (2014), who study how the presence of forward markets and of pivotal suppliers affects prices. None of these supply function experiments incorporates informational frictions.

Our experiment is also related to the literature of multi-unit uniform price auctions with incomplete information for which there is evidence of demand reduction—in demand auctions characterized by independent private values and an indivisible good—both experimentally (Kagel and Levin 2001) and in the field (List and Lucking-Reiley 2000; Engelbrecht-Wiggans et al. 2005, 2006). Outside the laboratory, Hortaçsu and Puller (2008) empirically evaluate strategic bidding behavior in multi-unit auctions using data from the Texas electricity market. These authors find evidence that large firms bid according to the theoretical benchmark while smaller firms deviate significantly from that benchmark. Unlike this literature, our paper addresses a uniform-price auction with interdependent values and a divisible good. The experiment we conduct is also related to that of Sade et al. (2006), who test the theoretical predictions of a divisible-good, multi-unit auction model under different auction designs; they report some inconsistencies between the theoretical equilibrium strategies and actual experimental behavior.

More indirectly, our results are related to findings in the literature on the winner's curse in single unit auctions where a bidder who is not savvy enough bids too aggressively, be neglecting that "winning" conveys the news that her signal was the highest in the market. The winner's curse is a prevalent, consistent, and robust phenomenon in single-unit auctions featuring common (or interdependent) values (Kagel and Levin 1986; Goeree and Offerman 2003; Kagel and Levin 2015). The analogy between the winner's curse in single-unit auctions with competition in supply functions may be relevant with respect to adverse selection but not necessarily with respect to market power.[5]

Several other papers study behavior in other contexts and show that individuals fail to extract information from other people's actions in various simpler contingent reasoning setups. Some examples of these contexts include bilateral negotiations (Samuelson and Bazerman 1985), in the acquiring a company game (Charness and Levin 2009), and voting (Esponda and Vespa 2014). In a simple financial market framework where traders submit limit orders, Ngangoué and Weizsäcker (2018) find that traders in simultaneous markets have difficulties in deriving information from hypothetical values of prices, while in sequential markets traders react to the price in a way that is consistent with a theory. In addition, in strategic games with private information, such as in Carrillo and Palfrey (2011) as well as Brocas et al. (2014) find that: (a) a large proportion of participants behave just as in the equilibrium where participants play simple but strategic private-information games yet (b) this proportion declines markedly with increasing strategic complexity of the game. In contrast to this literature, our experiment focuses on a complex environment which is a reflection of the environment that we examine – supply function competition with information frictions – and the results of simple experiments do not a priori extrapolate to complex ones.

3 Theoretical background and hypotheses

3.1 Theoretical background

We use the framework of Vives (2011). There are n sellers who compete simultaneously in a uniform price auction, and each seller submits a supply function. Seller i's profit is:

$$\pi_i = (p - \theta_i)x_i - \frac{\lambda}{2}x_i^2, \tag{1}$$

where x_i are the units sold, θ_i denotes a random cost parameter, p is the uniform market price, and $\lambda > 0$ represents a parameter that measures the level of transaction costs. The (random) cost parameter θ_i is normally distributed as $\theta_i \sim N(\mu, \sigma_\theta^2)$. The demand is inelastic and equal

[5] Our results are more closely related to the theoretical notion of the generalized winner's curse (Ausubel et al. 2014) which reflects that "winning" a larger quantity is worse news than "winning" a smaller quantity because the former implies a higher expected cost for the bidder (where bidders are sellers). In our environment a seller that faces a high price should think that it is likely that costs of her rivals are high and this is news that her own costs are also high because of the positive correlation. The result is that the seller should moderate her offer and this induces the supply function to be steeper. Therefore, rational bidders refrain from competing too aggressively.

to q, and the market-clearing condition allows us to find the market price p.

The information structure is as follows. A seller does not know the value of the cost shock θ_i before submitting her supply schedule, and she receives a signal $s_i = \theta_i + \varepsilon_i$ for which the error term is distributed as $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$, and hereafter assume that $\sigma_\varepsilon^2 > 0$. Sellers' random cost parameters may be correlated, with $\text{corr}(\theta_i, \theta_j) = \rho$ for $i \neq j$. Define the variance of the noise in the private signal over the variance of costs as $\phi \equiv \sigma_\varepsilon^2/\sigma_\theta^2$. Hence, the private signal is relatively precise (imprecise) in relation to the noise in the fundamental if ϕ is low (high).

Since the payoff function is quadratic and the information structure is normally distributed, Vives (2011) focuses on symmetric linear-Bayesian equilibrium. Linear supply functions are a reasonable approximation of the types of supply functions submitted by bidders in real markets.[6] Given the signal received, a strategy for seller i is to submit a price-contingent schedule, $X(s_i, p) = b - as_i + cp$. Thus the seller's supply function is determined by the three coefficients (a, b, c). We interpret these coefficients as follows: a is a bidder's response to the private signal; b is the fixed part of the supply function's intercept $b - as_i$; and c is the supply function's slope. Vives (2011) finds the unique linear symmetric supply function equilibrium (SFE) such that the first order condition satisfies:

$$X(s_i, p) = \frac{p - E[\theta_i \mid s_i, p]}{d + \lambda}, \tag{2}$$

where (a, b, c) are functions of the information structure (μ, ϕ, ρ) and market structure (n, q, λ) and $d = \frac{1}{(n-1)c}$ is the (endogenous) slope of the inverse residual demand for a seller.[7]

Let us focus on the equilibrium reasoning. Recall that $\sigma_\varepsilon^2 > 0$. If $\rho\sigma_\varepsilon^2 = 0$ then costs are uncorrelated and the seller does not learn about θ_i from the market price.[8] If $\rho\sigma_\varepsilon^2 > 0$ then costs are interdependent and the market price at the SFE has two roles as can be seen from (2): a) the market price is an index of scarcity, since a high equilibrium market price means that the seller has an incentive to increase her supply; b) it contains information about θ_i, since, if costs are interdependent, a rational seller should infer that a high price reveals that her cost is high (because $E[\theta_i \mid s_i, p]$ increases with p). Hence, if $\rho\sigma_\varepsilon^2 > 0$, then equilibrium supply functions are steeper in relation to when costs are uncorrelated. In this case, as either costs become more correlated (higher ρ) or private signals are less precise (higher ϕ) then the price is more prominent in the inference of θ_i, and equilibrium supply functions become steeper, leading to greater market power.

The condition that supply equals demand in equilibrium, $q = \sum_{i=1}^{n} X(s_i, p)$, yields the

[6]See, for example, Baldick et al. (2004).

[7]Throughout the paper, we shall often work with the inverse supply function since it corresponds more closely to how supply functions were represented in the experiment in the $(Quantity, AskPrice)$ space: $p = \hat{b} + \hat{a}s_i + \hat{c}X(s_i, p)$. Henceforth, we will omit the modifier "inverse" and refer simply to "the supply function".

[8]In the auction literature, the case when $\rho\sigma_\varepsilon^2 = 0$ is either referred to as independent values if values are uncorrelated, or to private values when signals are fully informative.

expected equilibrium price. The model predicts that equilibrium market outcomes are less competitive in markets with interdependent costs compared to markets with independent or private costs. As a consequence, the expected market price and profits of the equilibrium allocation can be shown to be higher in the former case than in the latter.

We use two classical measures of market power. The first is price impact, d, which can be defined as the slope of the inverse residual demand for a seller, which reflects the ability of a seller to influence the market price and measures unilateral market power.[9] At the SFE, price impact is equal to $d = \frac{\lambda(1+M)}{(n-2-M)}$, where $M = \frac{\rho n \sigma_\varepsilon^2}{(1-\rho)((1+(n-1)\rho)\sigma_\theta^2+\sigma_\varepsilon^2)}$ represents an index of adverse selection. Minimal market power obtains when $M = 0$ and M increases with ρ and with ϕ. When a seller faces a flatter (steeper) inverse residual demand, this means that her capacity to influence the price is low (high).

The second measure of market power that we use is the (interim) Lerner index, which shows the margin over average expected marginal cost. In equilibrium, the Lerner index for seller i is $L_i = \frac{p-E(\theta_i|\tilde{s})-\lambda x_i}{p}$, and when we average L_i for all the sellers of a given market we obtain the average Lerner index, L :

$$L = \frac{p - E(\tilde{\theta}|\tilde{s}) - \lambda(q/n)}{p}, \tag{3}$$

where $\widetilde{\theta} = \frac{1}{n}\sum_i \theta_i$ and $\widetilde{s} = \frac{1}{n}\sum_i s_i$.[10] The equilibrium market price is $p = E(\widetilde{\theta}|\widetilde{s})+(d+\lambda)\frac{q}{n}$, and it follows that in equilibrium: $L = d\left(\frac{q}{np}\right)$. In our predictions for the SFE, we use the average Lerner index given by (3), while in our empirical analysis we use the average (ex-post) Lerner index with the realized values of costs and experimental market price: $L' = \frac{p-\frac{1}{n}\sum_{i=1}^n \theta_i - \lambda(q/n)}{p}$.[11]

Comparing both measures of market power, we notice that price impact captures the extent to which a seller can influence the market price and mainly depends on sellers' supply function slopes. In contrast, the Lerner index, which is often used in empirical work, is a compound measure which takes into account the market price and the expected marginal cost given the signals received, and depends on sellers' supply function slopes and intercepts.

[9] The residual demand faced by a seller is the market demand not supplied by the other sellers in the same market. We use the inverse residual demand since we represent it in the $(Quantity, AskPrice)$ space. Price impact as a measure of market power has been used extensively in the financial economics literature, such as for example, by Kyle (1989).

[10] Average (interim) expected marginal cost is equal to: $\frac{1}{n}\sum_i E_i[MC_i] = E(\tilde{\theta}|\tilde{s}) + \lambda\tilde{x}$, where MC_i is the marginal cost of seller i and $\tilde{x} = q/n$.

[11] As it is common in the empirical literature, for the analysis of results we use the average Lerner index with the realized/actual values of costs. Notice that the average ex-post Lerner index over all the realized values of the experiment gives us an estimate for the (interim) average Lerner index.

3.2 Hypotheses

In our analysis of information frictions and market power, we first focus on the comparative statics of the SFE, and then consider its point predictions.[12]

Given the theoretical model, the SFE benchmark, we can formulate the following main hypothesis regarding market power and information frictions.

H1: *There is greater market power with interdependent costs than with uncorrelated costs.*

Hypothesis 1 is a consequence of the comparative statics of the SFE, which predict that, when costs are interdependent, the supply function will be steeper than when costs are uncorrelated, and for a given signal realization, the supply function's intercept is lower with interdependent costs than with uncorrelated costs.[13] These two factors imply that market power will be greater with interdependent costs than with uncorrelated costs.

We next formulate a stricter hypothesis relating each treatment to the point predictions made by the SFE.

H2: *Market power in each treatment aligns with the prediction made by the SFE benchmark.*

Finally, we formulate a hypothesis regarding the sensitivity of the supply function to the private signal.

H3: *The supply function slope does not depend on the private signal, while the supply function intercept reacts more to the private signal when it is more precise.*

This hypothesis is important in order to check whether the features of this class of models are observed in our experimental data, namely that the supply function's intercept depends on the private signal but that its slope does not, that is that supply functions are of the form $X(s_i, p) = b - as_i + cp$.

4 Experimental design and procedures

4.1 Experimental design

The experiment was based on the market environment described in the previous section. Each subject received a private signal and was subsequently asked to choose two *ask prices*: one for the first unit offered ($AskPrice1$) and one for the second ($AskPrice2$). We then used these two ask prices to construct a linear supply schedule, which was shown graphically on each subject's

[12] For other studies in experimental industrial organization that focus on the comparative statics of theoretical models, see Holt (1985) on quantity competition, Brandts et al. (2014) on supply function competition, Morgan et al. (2006) on price dispersion, Isaac and Reynolds (1988) on the relationship between spillovers and innovation.

[13] The relationship between cost correlation and market power may be different in other market settings. For example, in a second-price procurement auction of a single unit bidding, in the case of perfectly correlated costs, boils down to Bertrand competition, resulting in zero profits and hence zero market power. In contrast, when costs are independent, market power is strictly positive because the winner obtains the difference between the second-lowest and lowest cost.

screen.[14] The participant could revise the ask prices several times until she was satisfied with her decision. The demand was simulated. Once all supply schedules had been submitted, the auctioneer (the computer) calculated the uniform market price, and participants obtained feedback on own and rivals' performance and costs.

Conducting the experiment required us to specify numerical values for the theoretical model's fixed parameters. Our choices for the principal treatments are shown in Table 1. The selection of these values was based on three implementation criteria: (i) the existence of a unique equilibrium; (ii) sufficiently differentiated equilibrium behavior and outcomes between the treatments with different correlation levels and equal or similar equilibrium behavior and outcomes with the same correlation; and (iii) reduction of computational demands placed on participants.

The two principal treatments varied in the correlation among costs (ρ): treatment TUL had uncorrelated costs ($\rho = 0$), while treatment TCL had positively correlated costs ($\rho = 0.6$). We would have preferred to set a higher correlation among unit costs so that our predictions would be maximally differentiated. Yet inelastic demand reduces the range for which an equilibrium exists, and the highest correlation that satisfied our implementation criteria described earlier was $\rho = 0.6$. These two principal treatments had a relatively precise private signal with $\phi = 0.36$ in relation to the supplementary treatments, which investigate whether a higher noisiness of the private signal affects the competitiveness of markets (and these are presented in Section 6.3).

Table 1 describes the parameter values used in the principal treatments of the experiment.

Table 1: *Parameter values used in the principal treatments of the experiment.*

	Symbol	Value
Number of Sellers	n	3
Inelastic demand	q	100
Transaction cost parameter	λ	3
Mean of random cost	μ	1,000
Mean of signal's error	$\bar{\varepsilon}$	0
Variance of random cost parameter	σ^2_θ	10,000
Variance of signal's error	σ^2_ε	3,600
Variance of the noise in the private signal over the variance of costs	ϕ	0.36

We chose a market size of 3 because this is the minimum market size that does not lead to collusion in other, similar environments—for example, a Bertrand game (Dufwenberg and Gneezy

[14]Vives (2011) focuses on symmetric linear-Bayesian supply function equilibria, and we implemented this in our experiment by restricting participants to submit linear supply functions. In wholesale electricity markets and Treasury auctions bidders are allowed to bid non-linearly, and for experimental evidence see Bolle et al. (2013). This may facilitate collusion compared to our case since bidders could try to submit low bids on many units and very high ones on the units expected to determine the market price. Given the complexity of our experiment, we decided to stay close to the theoretical model for tractability, but exploring the relation between non-linear bidding and market power is certainly an issue worth studying in the future.

2000) and a Cournot market (Huck et al. 2004); Kwasnica and Sherstyuk (2013) document collusion in multi-unit auctions with two bidders but not with five bidders. Each independent group had 12 participants each, which consisted of 4 markets with 3 sellers in each market. Participants competed for 25 incentivized rounds in the principal treatments since it is an established fact that equilibrium does not appear instantaneously in experimental games. In all of these rounds, in order to keep the spirit of the theoretical model's one-shot nature, we employed random matching between rounds. Thus, the composition of each of the four markets varied each round within a group.

In addition, we imposed certain market rules, which were inspired by the theoretical model and facilitated implementation of the experiment. First, we asked each seller to offer all units for sale. Second, we asked sellers to construct a nondecreasing and linear supply function. Third, ask prices had to be nonnegative. Fourth, as mentioned above, we imposed a price cap in order to limit the potential gains of sellers in the experimental sessions. We told bidders that the simulated buyer would not purchase any unit at a price higher than 3,600 (price cap). The price cap was not part of the theoretical model, we chose a value high enough to preclude distortion of equilibrium behavior. Fifth, participants were given an initial endowment with which they could compensate losses during the duration of the session with the objective to speed up the learning process. If a subject had negative total profits in a given round, we allowed this subject to continue with the experiment since she could recover from losses in subsequent rounds before the end of the game.

At the end of each round, each participant received feedback on the uniform market price, her own performance (with regard to revenues, production costs, transaction costs, units sold, and profits), the performance of the other two market participants (units sold, profits, and supply functions), and the values of the random variables drawn (her own cost and the costs of the other two participants in the same market).[15] Participants were allowed to consult the history of their own performance. Other experiments have shown that feedback affects behavior in the laboratory. In a Cournot game, for example, Offerman et al. (2002) report that different feedback rules can result in outcomes that range from competitive to collusive. Given the complexity of our experiment, we maximized the feedback given after each round in order to maximize the potential learning of participants. After each participant had checked her feedback, a new round of the game would start. Note that, in each market and for each round, we generated three random unit costs from a multivariate normal distribution. Also, in each round and for each participant, the unit costs and signals were independent draws from previous and future rounds.

Given the experimental parameters, Table 2 shows the SFE predictions for various indicators

[15]Subjects did *not* receive feedback on the signal received by others because that would not be expected to occur in reality.

of behavior and market power.[16]

Table 2: *SFE predictions in the principal treatments.*

	TUL	TCL
Supply function	$p = 264.71+0.74s_i+6X$	$p = -204.06+0.86s_i+26.68X$
Supply function if $s_i = \mu$	$p = 1000+6X$	$p = 655.32+26.68X$
Price impact	3.00	13.34
Lerner index (interim)	0.084	0.29
Expected market price	1,200.00	1,544.68
Ex-ante expected profit	5,612.75	16,567.40

4.2 Experimental procedures

We ran the experiment with 384 participants, 144 of which participated in the principal treatments grouped in 72 participants for each of the treatments described in Table 1, and 240 participants who participated in the supplementary sessions. Each principal treatment had 6 independent groups of 12 members each. Participants competed for 2 trial rounds before the incentivized rounds to familiarize themselves with the context. At the end of the experiment, participants completed a questionnaire that requested personal information and asked questions about the subject's reflections after playing the game. Once the questionnaire was completed, each participant was paid in private.

Sessions were conducted in the LINEEX laboratory of the University of Valencia. The participants were undergraduate students in the fields of economics, finance, business, mathematics, engineering, and natural sciences.[17] All sessions were computerized.[18] Instructions were read aloud, questions were answered in private, and—throughout the sessions—no communication was allowed between participants. Instructions explained all details of the market rules, distributional assumptions on the random costs, the nature of signals, and the correlation among costs (the meaning of correlation was explained both with a definition and graphically). We tested participants' understanding with a pre-experimental comprehension test.

During the experiment participants won or lost points. At the end of the experiment, the total number of points were exchanged for euros at the rate of 10,000 experimental points per Euro. Each participant started with 50,000 experimental points.[19]The payments ultimately made to

[16]Online Appendix B explains how we calculated the variables in Table 2.

[17]As in most laboratory experiments, our subjects are university students. A natural question is how useful our data are to shed light on what happens in markets in which decisions are typically made by experience market traders. Fréchette (2015) surveys all the existing experimental studies in which the behavior of students and experts are compared. His overall conclusion is that: "(. . .), overall much of the big picture seems the same whether one looks at professionals or students in laboratory experiments testing economic models."

[18]For this purpose we used the *z-tree* software (Fischbacher 1999).

[19]An alternative to our payment scheme would have been to use the random-lottery incentive scheme and pay participants only the earnings of one period selected at random. This procedure has the potential of eliminating wealth effects that can arise when paying for all periods. At the same time, given that we have 25 periods, the

participants in the principal treatments ranged from 10 to 30.4 euros and averaged 22 euros.[20] Each session lasted an average of 2.5 hours. See Online Appendix A for the instructions, comprehension test, screenshots used for running the experiment, and the end-of-experiment questionnaire, and Online Appendix D for details of participants' demographic information.

5 Experimental results

In Section 5.1 we provide an analysis of the comparative statics between information frictions and market power, while in Section 5.2 we empirically evaluate the SFE prediction in each treatment and conduct a best-response analysis. Section 5.3 analyses the sensitivity of the supply function to the private signal. For comparability with the supplementary treatments, we use the first 18 rounds in all treatments. Further analysis on all the 25 rounds time trends and can be found in the Online Appendices C.1 and C.2.

5.1 Comparative statics of information frictions and market power

We use price impact and the Lerner index as our main measures for market power, and to get a more complete view, we also analyze the participant's supply functions, characterized by the intercept and the slope, market prices and profits in each of the treatments.[21]

Table 3 provides summary statistics of market power, which include the mean, standard deviation and median. Figure 1 shows the average supply function in each treatment, when decisions are averaged across all rounds, together with the corresponding theoretical benchmarks. We observe from Figure 1 that average supply functions in TUL and TCL are very close, and Table 3 shows that supply functions are even closer when looking at the median. In addition, we find that the average experimental supply function in the uncorrelated costs treatment (TUL) is close to the corresponding SFE benchmark, while in the interdependent costs treatment (TCL), observed behavior appears to be far from the SFE. These results bear some resemblance to the result presented in Goeree and Offerman (2003) in the context of a single-unit and a second-price auction comparing common versus uncorrelated private values, and to the winner's curse

probability of a particular period being chosen may be too small to have participants engage and focus their attention. In any case, note that we concentrate on a treatment comparison, which should not be affected by the specific features of the payment scheme. For an interesting discussion of different payment schemes see Bardsley et al. (2009).

[20] Given the length of the experimental sessions, we gave participants some additional euros ex-post to ensure that minimum earnings were 10 euros. In the principal treatments, there were only 3 subjects in TUL and 4 subjects in TCL that had a cumulated profit below zero for at least one round.

[21] We analyze bidding behavior in terms of the inverse supply function since it corresponds to how participants made their decisions: $p = InterceptPQ + SlopePQ\, X(s_i, p)$, where $InterceptPQ$ and $SlopePQ$ are the intercept and slope of the inverse supply function, respectively. For profits and the Lerner index, we used the ex-post measures with the realized values of costs. See Online Appendix B for more details.

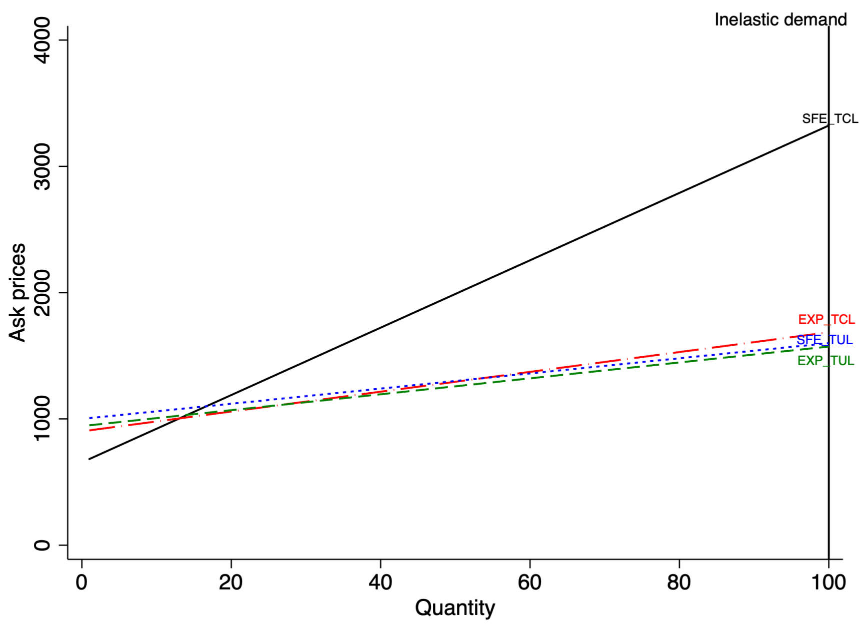
observed in common value auctions where bidders ignore the perfect correlation among costs (Kagel and Levin 1986).

Table 3: *Summary statistics of indicators of market power in each treatment.*

	TUL		**TCL**	
	Mean *(s.d.)*	*Median*	*Mean* *(s.d.)*	*Median*
Supply function	p = 943.01 + 6.30 X	p = 966.5 + 5 X	p = 901.35 + 7.85 X	p = 966 + 6 X
	(222.66) (5.48)		*(281.80) (6.89)*	
Price impact	2.74	2.31	3.38	2.73
	(2.05)		*(2.82)*	
Lerner index	-0.015	0.018	0.0072	0.024
	(0.40)		*(0.13)*	
Market price	1,109.14	1,121.00	1,123.10	1,135.50
	(125.79)		*(136.09)*	
Profit	2,134.91	1,542.28	1,875.44	1,666.02
	(7,810.99)		*(6,136.85)*	

Note. The second row after each variable in brackets and italics is the standard deviation (s.d.). The unit of analysis for price impact, supply function and profit is the individual choice in each round (there are 1,296 observations in each treatment except for price impact since it is not defined for 45 observations in the TUL and 31 in the TCL because of a null denominator). For the Lerner index and market price, the unit of analysis is the market with 432 in each treatment (in the TUL the Lerner index is not defined for 1 observation that as a market price equal to zero).

Figure 1: *Average experimental supply functions and theoretical benchmarks in each of the treatments.*



Note. SFE refers to the supply function equilibrium benchmark, and EXP to the average experimental supply function.

Observe in Table 3 that all the indicators of market power are very similar between the two treatments. Note that the average Lerner index in TUL is negative since it is influenced by a few large outliers which mainly occurred during the first four rounds: these had a very low market price due to some subjects placing very low ask prices. When testing the hypothesis that there is no difference in the indicators of market power at the aggregate level, we find no difference in any of the indicators of market power between treatments TUL and TCL. Using a Mann-Whitney-Wilcoxon rank-sum test (the unit of observation is the average per group, and there are 6 observations per treatment), the test results are: price impact (p-value=0.423); Lerner index (p-value=0.873); supply function slope (p-value=0.423) and intercept (p-value=0.749). In addition, we do not find differences in terms of market prices (p-value=1.000) and profits (p-value=0.423) between treatments.

We can summarize our findings with respect to H1 as follows:

Result 1 [Comparative statics related to market power and information frictions]:

Average market power is not statistically significantly different between TCL and TUL. This result is not consistent with our H1.

5.2 Empirical evaluation of the SFE point prediction

Our next analysis examines the specific point predictions made by the SFE with respect to market power in each treatment. Note that this is a very stringent test of the benchmark, and is not the primary focus of our investigation. We conduct this in two septs. As a first step, we use individual level data and run two random-effects panel regressions of the indicators of market power on the treatment dummy and controls (private signal and round) reported in Online Appendix C.3. As a second step, we use these regression results to carry out post-estimation t-tests of the equality of the regression's coefficients (the constant and treatment dummy) to the to the specific point prediction made by the SFE. The results obtained and presented in Table 4 allow us to statistically test whether the two indicators of market power accord to the SFE benchmark.

Table 4: *Statistical tests of the SFE point predictions regarding market power: p-values of testing price impact and Lerner index.*

SFE Benchmark	TUL p-values	TCL p-values
Price Impact	0.926	0.000***
Lerner Index	0.577	0.0086***

Note. The p-values presented in the table are the result of testing with t-tests the following hypotheses that follow from the regressions presented in Online Appendix C.3: in TUL that "constant=SFE prediction in TUL" while in TCL that "constant+treatment_dummy=SFE prediction in TCL". The tests are based on 2,516 observations for price impact and 863 for the Lerner index.

The results show that we cannot reject that the two indicators of market power are equal to the ones prescribed by the SFE in TUL, but we reject them in TCL. The next result sums up the evidence relating to H2.[22]

> **Result 2** [Tests of the point predictions of the SFE in each of the treatments]:
>
> *We cannot reject that average market power is consistent with the SFE predictions in TUL, but it is statistically significantly different from the SFE point predictions in TCL.*
>
> *Therefore, we reject H2 in TCL but not in TUL.*

We then conduct a best response analysis to see how actual profits compare to the ex-post optimal profits for subjects in each treatment. We compute ex-post optimal profits for a subject at a given round by calculating the optimal supply function that gives the highest possible profit given the choices of the rivals in this given round. We find the extent to which individual supply functions are a best response to the rivals' supply functions using detailed data of each round. We compute the differences between ex-post optimal profits and actual profits, and we refer to these differences as losses. The following table reports the results.

Table 5: *Summary statistics of losses (differences between ex-post optimal profits and actual profits) of all participants.*

Losses	TUL	TCL
Median	369.26	572.20
Min	0	0
Max	129,510	49,153

We find that median losses in TCL are 1.5 times larger than in TUL. This means that there is more sub-optimal behavior in TCL than in TUL, which might explain why we do not see a convergence towards the SFE prediction in this treatment.

5.3 Sensitivity of the supply function to the private signal

In order to further investigate how this result may be related to how individuals respond to the private signal, we next study how responsive the supply functions are to the private signal in each treatment. This analysis is important since the private signal is the input that subjects receive in each round, and in addition, it allows us to test whether the general features of the SFE model are observed in our experimental data. In particular, we want to test whether

[22] A test based on a first step regression without controls and simply with the constant and treatment dummy as explanatory variables rejects H2 for TUL. We believe that the regression including controls leads to a more appropriate test.

experimental supply functions have the structure proposed by the theory, that is, that the supply function intercept is sensitive to the private signal while its slope is not.

We run random effects panel regressions with the dependent variables supply function slope (*SlopePQ*) and intercept (*InterceptPQ*) on the private signal independent variable *(Signal)* and a treatment dummy (*D_ TCL*, which is 1 in TCL and 0 in TUL). These regressions cluster standard errors at the independent group level and are reported in Online Appendix C.3. As predicted by the theoretical model, we find that the private signal is not significant in the regressions of the supply function slope in neither of the treatments: coefficient on the signal (p-value=0.411) and on the treatment dummy (p-value=0.178).

However, the private signal does have a significant effect on the supply function intercept in each treatments: coefficient on the signal (p-value=0.000) and on the treatment dummy (p-value=0.346). There is no significant difference in how subjects respond to the private signal in either of the treatments. The next result summarizes our findings with respect to H3.

> **Result 3** [The responsiveness of supply functions to the private signal]:
>
> *The supply function slope is not influenced by the private signal, while the supply function intercept is responsive to the private signal in both treatments.*
>
> *This result is consistent with H3.*

The result suggests that the general features of the model are observed in the data. However, we do not find a difference in how supply function intercepts depend on the private signal in TUL and TCL. In TUL deviations from the SFE prediction are not large but in TCL these are substantial.

6 Possible explanations of our results

We consider three possible ex-post explanations of our results: alternative benchmarks (Section 6.1); Bayesian updating (Section 6.2); supplementary treatments which check whether our result may be related to the precision of the private signal (Section 6.3); and summary (Section 6.4).

6.1 Alternative benchmarks

Since the SFE point prediction does not explain the data well in TCL, we posit three alternative benchmarks and take them to the data. Note that for the SFE predictions, we have assumed that all sellers are perfectly rational, that they have common knowledge of the rationality of other players, and that they coordinate expectations on the SFE. We formulate our three alternative benchmarks by relaxing the two key factors of SFE (strategic behavior with respect to the competitive environment and optimal information processing) that lead to market power.[23]

A first possibility is that bidders are informationally naïve (hereafter, IN) since they do not extract information from the market price. This is equivalent to sellers ignoring the correlation among costs. This implies that $c^{IN} = \frac{n-2}{\lambda(n-1)}$ (since it is as if $M = 0$), the corresponding price impact is $d^{IN} = \frac{\lambda}{(n-2)}$. This benchmark is equivalent to the fully cursed equilibrium of Eyster and Rabin (2005) in our context.

A second possibility is that subjects are price takers (hereafter, PT) since they do not perceive the influence of their supply function decisions on prices, but condition on their private signal and learn from the price. This benchmark is equivalent to marginal cost pricing with sellers having the correct expectations about costs. The equilibrium supply function at the price-taking equilibrium (PT) has $c^{PT} = \frac{1}{\lambda(M+1)}$, which implies that $d^{PT} = \frac{\lambda(1+M)}{n-1}$.

A third possibility is that sellers are both price takers and informationally naïve (hereafter, PTIN). This is the case when agents ignore both strategic and inference effects. This is equivalent to marginal cost pricing with sellers having naïve expectations about costs (i.e. ignoring the correlation among costs). The equilibrium supply function slope for price-taking and informationally naïve participants (PTIN) has $c^{PTIN} = \frac{1}{\lambda}$, which implies that $d^{PTIN} = \frac{\lambda}{n-1}$. This benchmark combines the previously presented alternatives: IN and PT.

Note that apart from being conceptually well-defined there is some evidence consistent with both types of deviations from rationality behind our alternative benchmarks. For further empirical evidence on informationally naïve participants in other contexts refer to the Literature Review section. It is a priori reasonable that such informationally naiveness is also present in our setting. With respect to price-taking behavior, there are a number on experimental settings in which sellers do no fully exploit their market power. Holt (1995) finds that in quantity-setting experiments sellers set quantities above equilibrium levels. In an environment closer to ours, Abbink and Brandts (2005) find that in price competition with homogeneous goods, where sellers know own cost but not others' costs, pricing is more aggressive than in equilibrium.

Table 6 presents the price impact predictions of these alternative benchmarks together with the prescription of the SFE. Notice that if costs are uncorrelated then the price is not informative about costs and, hence, the PT and PTIN benchmarks are identical, and IN coincides with the SFE benchmark. In addition, we can see that market power is greater when sellers are strategic (i.e. in the SFE benchmark) than when they are price takers (i.e. in the PT benchmark). When costs are interdependent, sellers have the greatest market power when they are strategic and exploit the informational content of the price (SFE benchmark), followed by when sellers are strategic but informationally naïve (IN), followed by (under our parametrization) when sellers are price takers even if they exploit the informational content of the price

[23]For brevity, for the more detailed analysis in this section we focus on price impact.

(PT), and the smallest market power occurs in markets with fully naïve sellers (PTIN). Notice that the differences between PT, IN, PTIN are small. We find that in treatments with interdependent costs (TCL and TCH), the SFE predicts a substantially larger market power than all the alternative benchmarks, while in treatments with uncorrelated costs (TUL and TUH), the predictions of the SFE and alternative benchmarks are more similar.[24]

Table 6: *Price impact predictions for alternative benchmarks and the SFE in each treatment.*

TUL		**TCL**	
Benchmarks	**Price impact prediction**	**Benchmarks**	**Price impact prediction**
SFE = IN	3.00	SFE	13.34
		IN	3.00
PT = PTIN	1.50	PT	2.45
		PTIN	1.50

Table 7 presents the results of testing each of these benchmarks in the two treatments following the same approach as in Section 5.2 (the intermediate steps for this test are in Online Appendix C.3).

Table 7: *Statistical tests of the price impact point predictions: p-values of testing the SFE and alternative theoretical benchmarks.*

TUL		**TCL**	
Benchmarks	**p-values**	**Benchmarks**	**p-values**
SFE=IN	0.926	SFE	0.000***
		IN	0.218
PT=PTIN	0.0008***	PT	0.018**
		PTIN	0.000***

Note. The p-values presented in the table are the result of testing with t-tests the following hypotheses that follow from the regressions presented in Online Appendix C.3: in TUL that "constant=benchmark prediction in TUL" while in TCL that "constant+treatment_dummy=benchmark prediction in TCL". The tests are based on 2,516 observations.

Using price impact, the results show that in the TUL we cannot reject the SFE prediction (p-value=0.926), but we can reject that on average subjects behave according to the PT prediction. However, in TCL we reject the SFE, PT and PTIN predictions as benchmarks for describing average behavior, but we cannot reject that the IN benchmark describes the data well (p-value=0.218). This would suggest that the SFE fails in the TCL *not* because individuals are naïve with respect the (complex) competitive environment but because they are not sufficiently

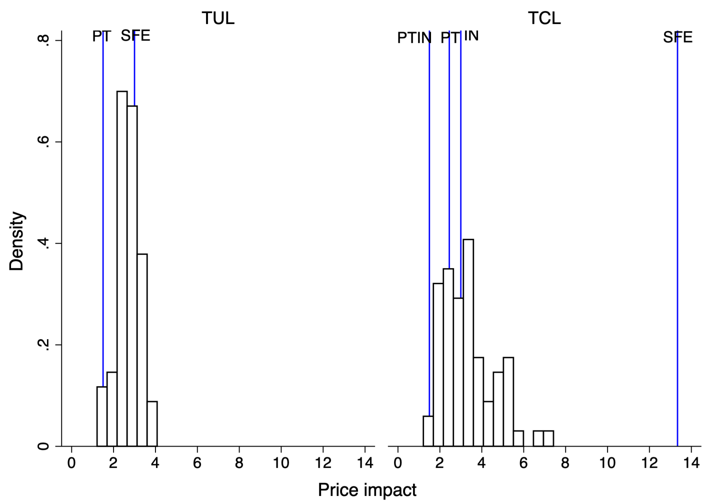
[24] Note that these three alternative benchmarks make similar predictions in the two treatments and so it might be empirically difficult to distinguish between them in these two treatments. We selected them on an a priori basis and not to fit the data.

sophisticated with respect to the information structure since they cannot make inferences from the market price. This results in outcomes that are much more competitive than predicted.

The previous result concerns average behavior. However, another interesting element to analyze is the dispersion in market power in each treatment, which is a result of the heterogeneous behavior of subjects in our experiment. For brevity, we use price impact in the rest of this sub-section. Figure 2 shows a histogram of the dispersion of price impact in each treatment.

Figure 2 shows that market power in the uncorrelated costs treatment is more homogeneous than in the interdependent costs treatment. We test this formally using Levene's test of homogeneity of variances where the unit of analysis is the same as in Figure 2, and obtain that we reject that variances are the same in TUL and TCL (p-value=0.000).

Figure 2: *Histograms for price impact for each subject in each treatment and the benchmarks.*



Note. The unit of analysis is price impact averaged over the 18 rounds for each subject (72 observations in each treatment).

To go one step further in our analysis of heterogeneity, in Online Appendix C.4 we report the results of estimating a mixture model estimation of the proportion of participants that have a price impact of each type. In the TUL, we find that 91% of the participants can be classified to be SFE types, while 9% can be classified as PT types. In the TCL, we find that 1% are PTIN, 48% are PT, 46% are IN, and 5% are SFE. Notice that in this treatment, we find that a large percentage of subjects do not engage in optimal behavior -either because they fail to take into account the correlation among costs or because they behave as if they were price-taking.

6.2 Bayesian updating

One could argue that participants fail to engage in Bayesian updating and that this is why, in treatment TCL, they fail to understand that the market price is informative about costs.

To explore this possibility further and to assist participants in the decision-making process, we conducted an supplementary treatment with 24 participants with two independent groups in the modified TCL treatment, hereafter TCL-Bayesian. The experimental design features were as in the baseline treatment but with three exceptions as follows. First, in addition to the signal received, each subject received the expected value of her own costs—and of her rivals' costs—conditional on the signal received (thus subject i received a signal s_i and was also given $E[\theta_i \mid s_i]$ and $E[\theta_j \mid s_i]$ for $i \neq j$).[25] Second, we explicitly asked each subject to think about what her rivals would do and provided a simulation tool that participants could use to make a provisional decision, based on those beliefs, and then visualize the resulting market price; the participant could then revise her decision. Third, the experiment lasted for 15 rounds due to time constraints.

Table 8 presents the summary statistics of behavior and outcomes in the TCL-Bayesian treatment. We find that the average supply function and outcomes in the robustness session are similar to the averages of the baseline treatments, presented in Table 3, that correspond to the TCL treatment. Our results in the TCL-Bayesian treatment suggest that the results in TCL are *not* simply due to a bias related to Bayesian updating.

Table 8: *Market power and information frictions in the TCL-Bayesian treatment.*

	TCL- Bayesian	
	Mean	*Median*
	(s.d.)	
Supply function	p = 898.46 +7.38 X	p = 937+5 X
	(212.94) (6.50)	
Price impact	3.13	2.61
	(2.13)	
Lerner index	-0.0052	0.013
	(0.27)	
Market price	1,115.66	1,114.50
	(122.70)	
Profit	2,007.11	1,509.69
	(6,621.62)	

Note. The second row after each variable in brackets and italics is the standard deviation (s.d.). The unit of analysis for price impact, supply function and profit is the individual choice in each round (there are 360 observations except for price impact since it is not defined for 8 observations because of a null denominator). For the Lerner index and market price, the unit of analysis is the market with 120 observations.

[25]The participant instructions for this supplementary treatment are available upon request. We explained conditional expectations by telling participants that, in each round, an expert would give them the expected value of both their and their rivals' unit cost.

6.3 Noisiness of the private signal

We developed ex-post supplementary treatments to investigate whether an increase in the variance of the noise of the private signal over the variance of costs (ϕ) affects the competitiveness of markets. Vives (2011) also gives us predictions on how the combinations the correlation among costs, ρ, and ϕ affect equilibrium market power.

In these two treatments, we increased ϕ: $\phi = 36$ with $\sigma_\theta^2 = 100$ and $\sigma_\epsilon^2 = 3,600$. We ran an uncorrelated costs treatment with $\rho = 0$ (TUH), and an interdependence costs treatment with $\rho = 0.175$ (TCH). For TCH, the combinations (ρ, ϕ) were chosen so that this treatment had similar level of market power to TCL, to make both treatments easily comparable. In addition, for $\phi = 36$ the equilibrium does not exist for any $\rho > 0.25$, and hence we chose $\rho = 0.175$ which, within the range of existence, has a very similar level of market power as TCL.[26] The SFE predictions for these two supplementary treatments are presented in Table 9. Notice that treatments TUH and TCH have a very similar predicted market power as TUL and TCL, respectively.

Table 9: *SFE predictions for treatments TUH and TCH*

	TUH	TCH
Supply function	$p = 972.97+0.027s_i+6X$	$p = 646.58+0.036s_i+25.04X$
Supply function if $s_i = \mu$	$p = 1000+6X$	$p = 682.72+25.04X$
Price impact	3.00	12.52
Lerner index (interim)	0.084	0.28
Expected market price	1,200.00	1,517.28
Ex-ante expected profit	5,000.23	15,576.1

Hypotheses 1 about the comparative statics of market power also applies to this setting. In particular, the SFE predicts that there is greater market power with interdependent costs (TCH) than with uncorrelated costs (TUH), and the market power is the same in treatments with uncorrelated costs (TUH and TUL) regardless of the noisiness of the private signal.

Table 10 presents the results of measuring market power in TUH and TCH, which can be compared to the main results presented in Table 3. The information contained in the table shows that average market power is generally greater in TCH than TUH, as predicted by the SFE comparative statics. We statistically evaluate it using a Mann-Whitney-Wilcoxon rank-sum test (the unit of observation is the average per group, and there are 6 observations per treatment), and we confirm it for: price impact (p-value=0.0065), Lerner index (p-value=0.0163), supply function slope (p-value=0.0039), supply function intercept (p-value=0.0039), market prices (p-value=0.016), and profits (p-value=0.055). However, the magnitude of the effect is small since average market power in TCH is substantially lower than predicted by the SFE.

[26] For robustness, Online Appendix E presents the analysis of an additional treatment (TCHH) with interdependent costs and a higher $\phi = 3600$.

We also statistically evaluate whether average market power is the same in treatments with uncorrelated costs (TUH and TUL) using the same procedure as above. We obtain that we cannot reject the prediction for price impact (p-value=0.337), Lerner index (p-value=0.2002), supply function slope (p-value=0.423), and supply function intercept (p-value=0.262). However, the evidence for profits is weaker (p-value=0.055), and we reject that market prices are the same in the two treatments with uncorrelated costs (p-value=0.016). Notice that we can also conclude that experimental behavior in TUH is close to the SFE benchmark.

Table 10: *SFE predictions in treatments TUH and TCH*

	TUH		**TCH**	
	Mean *(s.d.)*	*Median*	*Mean* *(s.d.)*	*Median*
Supply function	p = 929.87+6.64 X	p = 945+6 X	p = 790.74+11.54 X	p = 816+10 X
	(160.14) *(1.39)*		*(237.54)* *(7.38)*	
Price impact	2.90	2.73	4.89	4.52
	(1.39)		*(2.80)*	
Lerner index	0.017	0.020	0.036	0.037
	(0.059)		*(0.088)*	
Market price	1,122.37	1,124.00	1,149.31	1,141.50
	(60.96)		*(99.15)*	
Profit	2,090.08	2,046.12	2,983.52	2,697.51
	(2,762.76)		*(3,974.92)*	

Note. The second row after each variable in brackets and italics is the standard deviation (s.d.). The unit of analysis for price impact, supply function and profit is the individual choice in each round (there are 1,296 observations in each treatment, except for price impact since it is not defined for 11 observations in the TUH and 8 in the TCH because of a null denominator.) For the Lerner index and market price, the unit of analysis is the market with 432 in each treatment.

We can summarize our findings in the following result as follows:

Result 4 [Market power and the precision of the private signal]:

(i) If signals are imprecise then market power is statistically significantly higher with interdependent costs (TCH) compared to when costs are uncorrelated (TUH). However, the magnitude of the difference is small.

(ii) As predicted, there is no significant difference in average market power between markets with uncorrelated costs (TUL and TUH) regardless of the noisiness of the private signal.

To sum up, we find that market power is statistically significantly larger with interdependent costs and more imprecise private signals in relation to when costs are uncorrelated and private signals are more accurate. However, the magnitude of the difference is small compared to the magnitude of the predicted difference. When subjects are given more imprecise private signals then the inference problem of extracting information from the market price seems to becomes less severe, but not enough so as to lead to a substantial increase in market power.

6.4 Overall summary of possible explanations of our results

In this section we have investigated three possible explanations of our results. Our findings suggest that, in interdependent cost treatments the divergence between average behavior and the SFE predictions is related to participants' lack of sophistication with respect to the information environment. A further exploration of heterogeneity shows that a large percentage of subjects in TUL behave as prescribed by the SFE, while in the TCL there is a large divergence from what is predicted, either because subjects ignore the correlation among costs or because they behave as price takers. We find that this is not due to a bias related to simple Bayesian updating but it is related to the fact that, on average, subjects neglect the information conveyed by the market price and this translates into lower observed market power. In the supplementary treatments subjects are given more imprecise signals. We find that, on average, in these treatments market power is statistically significantly higher with interdependent costs compared to uncorrelated costs perhaps because they focus less on their private signal and more on the market price.[27]

7 Concluding remarks

We have analyzed bidding behavior in a theory-based experimental setting that reflects some of the complexity of real-world markets where bidders compete in supply functions, have incomplete information about their costs, and receive a noisy private signal. We focus on the comparative statics of the supply function equilibrium (SFE) to study our experimental results. We also consider alternative benchmarks resulting from relaxing the assumptions of the SFE. We used two principal and two supplementary treatments that vary in the correlation among costs and the precision of the private signals in relation to the precision of costs. In the principal treatments private signals are more precise than in our supplementary treatments.

Our experimental results document certain causal relations between information frictions and market power in the context of supply function competition. Contrary to our hypothesis, in our principal treatments average market power in markets with interdependent costs is the same as with uncorrelated costs. In the supplementary treatments with relatively noisier private signals than in the principal treatments, we find that interdependent costs lead to a statistically significant but small increase in market power, much smaller than predicted by the SFE.

We can connect our results to policy considerations pertaining to natural markets like the wholesale electricity market or Treasury bond auctions. We observe low market power in our four treatments. Since in our setting explicit collusion is excluded by design our results with interdependent costs and precise private signals would suggest that the observation of high

[27]These results might be related to the fact that when there are two sources of information (the private signal and the price), the relatively quality of these two sources of information may matter for the agents' attentiveness when they have a limited capacity to process information (Kacperczyk et al. 2016).

prices in natural markets would point to the existence of some kind of collusion.[28] Overall, competition authorities may want to fine-tune their collusion screening procedures by taking into account the information structure of the market, in particular cost correlation, in settings with supply function competition. We find some evidence that an increase in the precision of private signals leads to a decrease in market power. This results suggests that any increase in transparency that translates into lowering the noise in the private signals would lead to a small pro-competitive effect.[29]

Our experiment suggests additional questions for future research, both experimental and theoretical. An important extension of our work would be to allow bidders in the experiment to submit non-linear supply functions. Additional future work could explore mechanisms by which participants learn how to improve information extraction from the price (e.g., asking participants to come back to the laboratory a few days later -experienced bidders; replicating the experiment with professional traders). Increased capacity to learn from the price would imply a potential higher exercise of market power. The experimental findings reported here also call for the development of theoretical models that analyze market competition among participants who exhibit various degrees of sophistication in markets characterized by supply function competition and private information.

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[28]Observe that since we implement a one-shot game by using random matching, the emergence of tacit collusion, like the one observed in Byrne and de Roos (2019) is not possible in our environment.

[29]However, see Luco (2019) for a study with observational data that shows that transparency can also lead to higher margins because of a collusive effect.

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