Spatial competition with demand uncertainty: A laboratory experiment

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Spatial Competition with Demand Uncertainty: A Laboratory Experiment

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Abstract

Motivated by recent research on product differentiation, we conduct laboratory experiments to study how (aggregate) demand uncertainty influences location choices and price competition in the original Hotelling (1929)'s model. We provide new predictions on the effect of risk attitudes on both decisions under demand uncertainty and confront them with the data. Our experimental results support the predictions that demand uncertainty acts as a differentiation force for risk-neutral and risk-lover subjects. By contrast, we do not verify that demand uncertainty leads risk-averse subjects to agglomerate. This is explained primarily by learning effects and heterogeneous behaviors within this risk profile. Finally, we observe various price-setting behaviors, ranging from an attempt to collude to a price war, depending on the level of differentiation.

Keywords: product differentiation, demand uncertainty, price competition, experiment

JEL Classification: C72, C91, D43, L13, R30

Concurrence spatiale et incertitude de la demande : une expérience en laboratoire

Résumé A la suite de récents travaux sur la différenciation des produits, nous étudions comment l'incertitude sur la demande (au niveau agrégé) peut altérer les choix de localisation et de concurrence en prix dans le modèle standard de concurrence spatiale à la Hotelling (1929). La prise en compte de préférences hétérogènes vis-à-vis du risque conduit à l'obtention de prédictions théoriques nouvelles sur les choix de localisation et de prix. La validité de ces prédictions est ensuite testée empiriquement à partir de données collectées via une expérience en laboratoire. Les résultats expérimentaux confirment la prédiction selon laquelle une incertitude sur la demande agit comme une force de différenciation pour des sujets neutres au risque ou risquophiles. A l'inverse, et contrairement à la prédiction du modèle, il n'est pas observé que les sujets averses au risque s'agglomèrent plus fortement en présence d'une incertitude sur la demande. Ceci s'explique principalement par des effets d'apprentissage et des comportements hétérogènes au sein de cette catégorie de sujets. Enfin, nous observons des comportements de fixation de prix très variés en fonction du niveau de différenciation, allant de la (tentative de) collusion à la guerre de prix.

Mots-clés : différenciation des produits, incertitude de la demande, concurrence en prix, expérience.

Classification JEL: C72, C91, D43, L13, R30

Spatial Competition with Demand Uncertainty: A Laboratory Experiment

1. Introduction

Product success hinges principally on a firm's ability to meet demand. Although easily stated, firms face considerable difficulties in practice in envisioning how consumers will appreciate a brand new product. Recent examples of product failures, such as Google Glass or the Amazon Fire Phone, illustrate this complexity. Such poor design or unsuitable product features may have dramatic consequences for the financial health of firms. Firms thus cite addressing demand uncertainty as one of the key challenges on the road to success (see Capgemini Consulting, 2012, for instance). Launching a new product is indeed a complicated task because firms are uncertain about consumer tastes and have to choose which bundle of characteristics to offer, while anticipating rivals' reactions. In essence, firms could respond to this uncertainty by offering either innovative and differentiated products, to relax price competition, or basic products, and thus compete head-to-head with their rivals.

Based on the seminal model of Hotelling (1929), we conduct laboratory experiments to empirically examine to what extent demand uncertainty influences firms' incentives to differentiate. Further, by testing Hotelling's original location-then-price game in the lab, we are able to study the pricing behavior of firms facing different levels of differentiation. In doing so, we provide new empirical insights into how demand uncertainty shapes product differentiation strategies and, thus, the intensity of competition. This is of particular interest because demand uncertainty may lead to market outcomes that are far from the social optimum.

Until recently, product differentiation (in characteristics or in geographical space) was long analyzed in the Industrial Organization literature through the use of Hotelling-style location models with the assumption that firms have perfect knowledge about demand. In short, this vast literature teaches us that under a wide range of assumptions, firms tend to differentiate along the *dominant* characteristic to soften price competition (see, *e.g.*, Irmen and Thisse, 1998).[1] Surprisingly, this result has found little empirical support. Among the few attempts at empirical validations, mixed evidence of clustering and dispersion has been found, thus casting doubts on the validity of the "principle of maximum differentiation".[2]

[1] Nonetheless, it is well established that it is possible to obtain all sorts of equilibrium outcomes in the one-dimensional case, ranging from minimal to maximal differentiation, depending on the model's assumptions (see, *e.g.*, Brenner, 2001 for a survey on Hotelling-style models of product differentiation).

[2] These studies are typically conducted in markets where the geographical dimension is predominant. For instance, Schuetz (2015) shows that Big Box retailers prefer to agglomerate in desirable locations rather than cede market shares to rivals (see also Eckert *et al.*, 2013 for a location study of shopping centers), whereas Netz and Taylor (2002) find that gasoline stations spatially differentiate more when the intensity of competition increases (see also Seim, 2006 for a study of the video retail industry). Less extreme results are found by Elizalde (2013), who observes both location equilibria in the movie theater industry.

In recent years, few authors have revisited the results of the location-then-price game of Hotelling's model, assuming firms are uncertain about (aggregate) consumer tastes (see, *e.g.*, Harter, 1996; Casado-Izaga, 2000; Meagher and Zauner, 2004, 2005). Interestingly, this stream of research has demonstrated that firms differentiate more when facing demand uncertainty than when they are perfectly informed.[3] Further, these studies have shown that the differentiation force is increasing in the level of uncertainty, suggesting that in markets with fast-evolving tastes, such as the apparel industry, one would observe more differentiation among products.[4]

Empirically testing the effect of demand uncertainty on firm differentiation strategies is, however, a non-trivial task. As in the case in which consumer tastes are assumed to be known by firms, it is difficult to define a relevant proxy for product differentiation while being able to control for exogenous market constraints that could bias the measure (*e.g.*, geographical boundaries or demographic factors in the retail industry; see Picone *et al.*, 2009). Furthermore, accounting for demand uncertainty introduces an additional difficulty: how should one assess the level of uncertainty encountered by firms? For all these reasons, using laboratory experiments seems the appropriate solution to study firms' incentives to differentiate when facing demand uncertainty.

Past experiments have studied endogenous location choices or pricing decisions in spatially differentiated markets, but they always assume that one or the other of these decisions is exogenous. Brown-Kruse *et al.* (1993) and Brown-Kruse and Schenk (2000) analyze firms' location decisions in repeated spatial duopoly markets with elastic demand and a fixed price environment. Both studies demonstrate that subjects tend to agglomerate at the center of the market (*i.e.*, the non-cooperative equilibrium), but subjects succeed to coordinate and achieve the collusive outcome when non-binding communication is introduced (*i.e.*, firms locate at the quartiles of the market). Huck *et al.* (2002) confirm the attractiveness of the central location in a quadropoly market with inelastic demand, while Collins and Sherstyuk (2000) emphasized the role of risk attitudes to explain deviations from the Nash-equilibria in a triopoly market. In another vein, Orzen and Sefton (2008) empirically analyze a spatial price competition model under the assumption of exogenous firm locations. They report persistent price dispersion in accordance with mixed strategy equilibria.

To our knowledge, only two works have tested in the lab a two-stage model of location decisions and price competition. The earlier paper of Camacho-Cuena *et al.* (2005) is, however, rather specific, as it also includes an endogenous consumer location choice stage, which enables the authors to revisit the issue of product differentiation in the presence of strategic buyers. More closely related to our study is that of Barreda-Tarrazona *et al.* (2011). Their experimental design recasts the spatial duopoly model of Hotelling (1929) in a discrete framework with linear disu-

[3]A similar result is found by Cheng (2014) when firms are vertically differentiated and uncertain about how consumers perceive products' quality.

[4]Note that the effect of demand uncertainty is reversed when uncertainty is introduced at the individual level through idiosyncratic shocks to consumer tastes (see de Palma *et al.*, 1985; Anderson *et al.*, 1992).

tility of transportation and few demand slots. They find that subjects differentiate significantly less than predicted, thus providing support for the principle of minimum differentiation. One advantage of their experiment is that it delivers closed-form solutions of the theoretical model. We thus depart from their framework and extend it by introducing demand uncertainty through a random shift of the support of the linear city as in Meagher and Zauner (2005). Subjects simultaneously choose their location before the location of the consumer distribution is revealed and then compete in prices with perfect knowledge about demand location. We implement three experimental treatments. In the baseline treatment, subjects have perfect information on demand location, whereas in the other two treatments, they face different levels of demand uncertainty.

Our empirical results confirm that, on average, demand uncertainty acts as a differentiation force, a finding that supports the theoretical predictions of past studies. However, we observe that most of subjects locate close to the center regardless of the treatment, thereby leading to a level of differentiation far below that derived in the non-cooperative equilibrium. For such levels of differentiation, it appears that subjects attempt to collude in prices. Conversely, for higher levels of differentiation, we find that subjects set prices close to the non-cooperative equilibrium. Altogether, the posted prices attest to the standard positive relationship between differentiation and prices when demand location is perfectly known.

In addition, our experimental setting offers a suitable environment to study how non-risk neutral subjects would react to the introduction of demand uncertainty. While the effects of risk aversion on firms' decisions seems central in a context of demand uncertainty, this issue has thus far been neglected in the literature.[5] We first derive new theoretical predictions on the effect of demand uncertainty on firms' decisions in the location-then-price game. In particular, we show that demand uncertainty leads risk-averse firms to agglomerate to secure (a lower) part of demand, unlike risk-neutral and risk-lover firms. Then, we control for subjects' risk attitudes in the lab by means of a second experiment that elicits individual levels of risk aversion (Drichoutis and Lusk, 2012). Examining the results by risk profile, we find that risk-neutral and risk-lover subjects differentiate more when demand uncertainty increases. This result is, however, at odds with the game predictions for risk-averse subjects, and we provide some explanations for the observed differences.

The remainder of the paper is organized as follows. Section 2. presents the discrete framework of the location-then-price game and reports the game equilibria for the different treatments. Section 3. describes the experimental design, and the results of the experiments are reported in Section 4.. Finally, Section 5. concludes.

[5]One exception is Balvers and Szerb (1996), who analyze the location choices of risk-averse firms in a spatial duopoly model featuring aggregate demand uncertainty. However, prices are assumed to be exogenous in their model, which entails the standard result of firms locating at the center in the absence of uncertainty. When uncertainty arises, an increase in risk aversion drives firms closer to the edges of the city to secure a smaller share of demand and avoid risky realizations of the random shock that decrease expected payoffs at the city center.

2. A Discrete Version of the Hotelling Game

We present in Section 2.1. a discrete version of the standard Hotelling's model. We first derive the game equilibria under the assumption of perfect knowledge about demand location and risk-neutral firms in Section 2.2.. We then introduce demand uncertainty in Section 2.3.. Finally, we relax the hypothesis of risk-neutral firms in Section 2.4..

2.1. Basic Settings

As a natural benchmark, we consider the standard Hotelling model in which firms play a location-then-price game under the canonical assumptions that firms are risk-neutral and demand is perfectly known by firms (hereafter denoted as the *demand certainty* case) prior to their location and price decisions.[6] To conduct experiments in the lab, we recast the Hotelling (1929) model in a discrete framework. To this end, we borrow from the game proposed by Barreda-Tarrazona *et al.* (2011) and extend their baseline case to introduce demand uncertainty. While using a discrete framework makes it difficult to derive closed-form solutions, it also allows us to limit both the number of locations and price offers. This provides two advantages: it favors the replication of the game in the lab, and facilitates the comparison with real-world situations in which the sets of actions are reduced. In the next paragraphs, we present the key features of the game proposed by Barreda-Tarrazona *et al.* (2011), and introduce specific notations that will be useful when adding demand uncertainty.[7]

There are two firms $i = \{1, 2\}$ playing a location-then-price game. In the first stage, firms simultaneously choose their location with perfect information about demand. Once the locations are set, firms compete simultaneously in prices. The optimal solution of this game can be derived through the resolution by firms of the profit maximization problem given by $\Pi_i\left(x_i, p_i\right) = \max\left\{p_i \cdot q_i\right\}$, where p_i denotes the price charged by firm i and q_i its residual demand.

Assume there is a unit-length linear segment populated by 7 consumers $j = \{1, \ldots, 7\}$ uniformly distributed over $[M-3, M+3]$, where M denotes the city center and $M \in \Re$. As shown in Fig.1, each consumer is located on one of the 7 equidistant slots denoted $x_j \in \Re$.[8] A consumer can either buy a maximum of one unit of the good sold by one of the two firms labeled i and located at $x_i \in \Re$ or abstain from buying. Without loss of generality, we assume that firm 1 is located to the left of firm 2, *i.e.* $x_1 \leq x_2$. Firms sell a homogeneous good produced

[6] To be as close as possible of the pioneering work of Hotelling (1929), we also assume that consumers are uniformly distributed over the linear city, firms' location are restricted to the inner city, travel costs are proportional to distance traveled, and demand is inelastic up to a reservation price.

[7] Readers interested in a more detailed presentation of the baseline model are referred to Barreda-Tarrazona *et al.* (2011)

[8] Throughout the paper, we only consider the *Simulated Consumers Treatment* of Barreda-Tarrazona *et al.* (2011), which implies an odd number of locations and exogenous consumers.

with constant marginal costs normalized to 0. Since the product is not vertically differentiated, the sole difference between the levels of appreciation is based on a consumer tastes for the ideal product defined in terms of its geographical location (or product characteristic). Hence, for a consumer located at x_j who visits firm i, his indirect utility function is given by:

$$V_{ji} = R - p_i - tx_{ij} \tag{1}$$

where R is the basic reservation utility, which is assumed to be positive, p_i is the price charged by firm i, x_{ij} represents the distance between firm i and consumer j (*i.e.*, $x_{ij} = |x_i - x_j|$), and t is a transportation cost per unit distance. According to the highest utility rule, consumer j purchases the product from firm i, if $V_{ji} > V_{jk}$ where $k \neq i$. In other words, consumer i chooses the cheapest firm (*i.e.*, the firm with the lowest mill price plus transportation cost), as long as his payment does not exceed his reservation utility R. In the event of ties between V_{ji} and V_{jk}, the consumer is assumed to randomly choose one of the two firms with probability 1/2. Bearing in mind that the experiment should be kept as simple as possible, we adopt the same parameter values as Barreda-Tarrazona *et al.* (2011), which entails clear-cut solutions for experimental subjects. Therefore, we set $R = 10$, $p_i = \{1, \ldots, 10\}$ and $t = 6$.

At this point, two central hypotheses of the model must be discussed. First, by specifying a linear transportation cost, we elected to promote the simplicity of the experimental design at the expense of obtaining pure-strategy equilibrium prices. Clearly, it appears less computational demanding for subjects to determine their payoff when the disutility of buying a product that is not the desired product is represented by a linear function rather than a quadratic function. Therefore, we expect that a linear form reduces the risk that subjects will switch from a rational behavior to a fuzzy behavior. However, a number of theoretical works have long demonstrated that the original (continuous) Hotelling location-then-price game with linear transportation costs leads to no equilibrium price solution in pure strategy (d'Aspremont *et al.*, 1979; Economides, 1986). With a linear transportation cost, profit functions are no longer quasi-concave, which entails discontinuity in the best response functions and, thus, the non-existence problem. However, by discretizing the Hotelling game, we have already introduced discontinuity into the firms' profit function. Thus, adopting a particular specification of the transportation cost is less critical for the existence of a unique price equilibrium in pure-strategy.

Second, and unlike previous experiments based on spatial competition models (see, *e.g.*, Brown-Kruse and Schenk, 2000; Collins and Sherstyuk, 2000; Huck *et al.*, 2002; Orzen and Sefton, 2008), the resolution of the game yields possible outcomes in which the market is not fully covered. This particularity originates from the parametrization of the model that enables firms to set delivered prices that exceed the consumer's reservation utility. At these prices, consumers are thus better off not buying the good, thereby resulting in an uncovered market. As a consequence, in the particular case in which non-buying consumers are located between the

Table 1: Price Equilibrium Payoffs for each Pair of Locations (Demand Certainty)

	1	2	3	4	5	6	7
1	(3.5,3.5)^e	(1,6)	(4.71,15.88)*	(10,22.42)*	(18,28)	(21,28)	(24.5,24.5)^e
2	(6,1)	(3.5,3.5)^e	(2,5)	(10,17)*	(20,23.65)*	(24.5,24.5)^e	(28,21)
3	(15.88,4.71)*	(5,2)	(3.5,3.5)^e	(6,8)	(18.2, 18.2)*	(23.65,20)*	(28.18)
4	(22.42,10)*	(17,10)*	(8,6)	(3.5,3.5)^e	(8,6)	(17,10)*	(22.42,10)*
5	(28,18)	(23.65,20)*	(18.2,18.2)*	(6,8)	(3.5,3.5)^e	(5,2)	(15.88,4.71)*
6	(28,21)	(24.5,24.5)^e	(20,23.65)*	(10,17)*	(2,5)	(3.5,3.5)^e	(6,1)
7	(24.5,24.5)^e	(21,28)	(18,28)	(10,22.42)*	(4.71,15.88)*	(1,6)	(3.5,3.5)^e

Notes: $(\star)$ and (e) denote mixed strategy equilibrium and expected payoffs due to indifferent consumers, respectively.

two firms, the firms do not directly compete with one another but instead behave like local monopolists.

2.2. Location-then-Price Game Equilibria

Throughout the paper, we study the non-cooperative equilibrium of the game and we consider a subgame perfect Nash equilibrium (SPE) as the equilibrium concept.[9] Note further that the theoretical predictions and results are expressed in terms of consumer location for ease of exposition.

Price equilibria are determined for each pair of locations (x_1, x_2). Whenever a consumer is indifferent between firms 1 and 2, we adopt an arbitrary sharing rule, such that the marginal consumer chooses one of the two firms with probability 1/2. In the case of a multiplicity of price equilibria, we assume that firms choose the riskless option, meaning the price equilibrium that ensures an equivalent level of profit with a safe number of consumers. In other words, firms are assumed to be ε-risk averse. Finally, if multiplicity of equilibria persists, firms choose the Pareto superior equilibrium, and otherwise the joint profit-maximizing solution. Assuming that firms are risk-neutral and perfectly informed about demand location, we report in Table 1 the payoffs derived from the price equilibrium for each pair of locations.[10] Given the matrix of payoffs, it is now easy to determine the unique SPE of the location-then-price game under demand certainty (labeled DC hereafter).

Proposition 1 *The unique SPE locations for the location-then-price game under demand certainty and risk neutrality is* $(x_1^\star, x_2^\star) = (2, 6)$ *with equilibrium prices* $(p_1^\star, p_2^\star) = (7, 7)$.

This result, first established by Barreda-Tarrazona *et al.* (2011), entails a degree of differentiation equal to $\Delta^{DC} \equiv x_2^\star - x_1^\star = 4$.

[9] We study in Appendix D the cooperative equilibrium of the game under the assumption of tacit collusion between firms.

[10] We provide some explanations of the computation of the price equilibria and report the price equilibrium for each pair of locations in Appendix A.

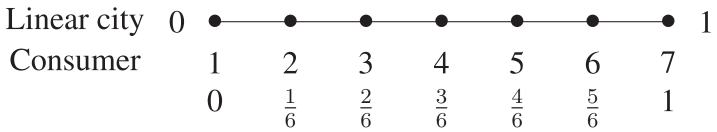


Figure 1: Demand Certainty treatment $(L = 0)$: Linear city with 7 consumers and 7 potential locations.

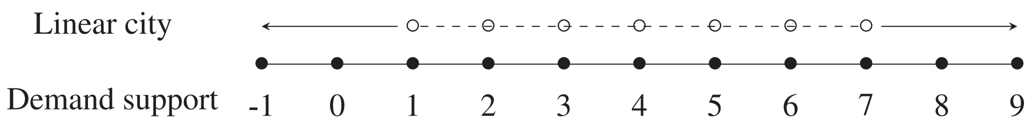


Figure 2: Low Demand Uncertainty treatment $(L = 4)$: Linear city with 7 consumers and 11 potential locations.

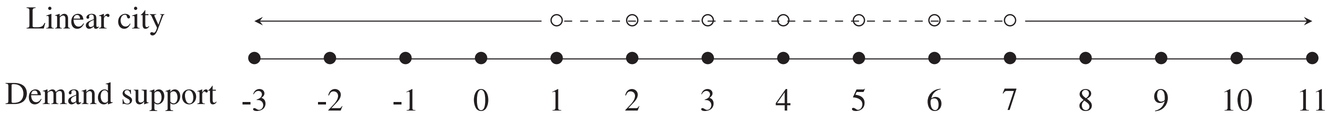


Figure 3: High Demand Uncertainty treatment $(L = 8)$: Linear city with 7 consumers and 15 potential locations.

2.3. Demand Uncertainty

We now introduce demand uncertainty into the location-then-price game under the assumption that firms are risk-neutral. This extension corresponds to the central issue of the paper that we aim to experimentally investigate. The introduction of demand uncertainty echoes a recent and growing stream of research that investigates to what extent uncertainty over (aggregate) demand location mitigates firms' positioning in geographical space. In brief, this literature considers a modified version of the (continuous) Hotelling game in which uncertainty applies to consumer locations through a random shift of the support of the linear city. For instance, Casado-Izaga (2000) departs from the standard location-then-price game with quadratic transportation costs, and models demand uncertainty as a common draw of the mean of the consumers' distribution, which is assumed to be uniformly distributed.[11] For simplicity, the center of the linear city is assumed to be drawn from a uniform distribution on the closed unit interval $[0, 1]$ and revealed to firms once the simultaneous location game has ended. Meagher and Zauner (2005) generalize this setting by extending the support of the distribution of the city center to $\left[-\frac{L}{2}, \frac{L}{2}\right]$, where L represents the size of the uncertainty. They show that a unique pure-strategy SPE exists that leads to higher expected prices, higher differentiation, and higher expected profits when L increases.

The intuition for this result is simple. Under demand uncertainty, the equilibrium of the Hotelling game is shaped by the basic tradeoff that firms face between securing a larger fraction of demand by locating close to the center (*demand effect*) or relaxing price competition by moving farther away from its competitor (*strategic effect*). In the presence of uncertainty about consumer locations, this tradeoff is altered, such that firms are more interested in relaxing price competition. Specifically, assuming a uniform distribution of uncertainty, extreme realizations of demand have an equal chance of occurring as do central realizations. This implies that firms are no longer certain to lose consumers when locating far away from the center. Consequently, the demand effect is weakened, and this leads firms to differentiate themselves to reduce price competition. This result is more pronounced the greater the level of uncertainty.

Although established for a given set of assumptions, the differentiation force entailed by demand uncertainty remains valid under alternative assumptions: a non-uniform distribution of the random shock (Meagher and Zauner, 2004, 2008, 2011),[12] sequential location choices (Harter, 1996; Casado-Izaga, 2000; Bonein and Turolla, 2009), and pricing decisions under demand uncertainty (Meagher and Zauner, 2004, 2005).

To experimentally test the effect of demand uncertainty on firm differentiation, we extend the

[11] Readers interested by a more general setting in which uncertainty arises at the distributional level and does not rely on the first moment of the distribution alone are referred to Meagher and Zauner (2004, 2008).

[12] In a previous work, Meagher and Zauner (2004) investigate the case of a random shock originating from a non-uniform density function. In this former model, firms' beliefs rely only on the first two moments of the distribution of the city center, but the support of the uncertainty is restrained to $\left[-\frac{1}{2}, \frac{1}{2}\right]$ to ensure market coverage.

baseline model by now assuming that firms are uncertain about consumer locations. The timing of the game is as follows. Firms simultaneously choose their location without having knowledge about the location of demand. Then, the demand uncertainty is revealed, and location choices are publicly announced. Finally, firms simultaneously set their prices. We follow Meagher and Zauner (2005) by assuming that firms are uncertain about the realization of the first moment of the consumer distribution, while being perfectly informed of the higher-order moments of the distribution and the definition of its support. Implicitly, this implies that firms' beliefs are represented by a common prior.[13] Formally, let us assume that M is distributed according to a discrete uniform distribution on $\left\{-\frac{L}{2}+4,\ldots,4,\ldots,\frac{L}{2}+4\right\}$, with $L > 0$. To facilitate comparisons among treatments, we impose that the central location is always the integer 4 whatever the extent of the uncertainty. The expected profits of firm i for a given pair of locations (x_i, x_{-i}) and prices (p_i, p_{-i}) are now given by:

$$\mathbb{E}\left[\Pi_i\left(x_i, x_{-i}, p_i, p_{-i}|M\right)\right] = p_i \times \left[\frac{1}{M_C} \times \sum_c q_{ic}\left(x_i, x_{-i}, p_i, p_{-i}|M\right)\right] \tag{2}$$

where c is a realization of the random variable M, M_C is the number of possible realizations of M, and $q_{ic}\left(\cdot\right)$ denotes the consumer who is indifferent between the two firms for the realization c of the city center. Note that since the city center M is distributed uniformly, the formulation of the expected profits gives equal weight to each realization of M in the computation of the firm's demand.

In the experiment, we consider two treatments that embody demand uncertainty and differ in the extent of the uncertainty. In a first treatment, we investigate firm decisions under a high level of uncertainty about consumer locations by setting $L = 8$. This treatment, labeled *High Demand Uncertainty* (HDU), increases the support of the distribution of consumers, thus offering 9 possible realizations for the city center M.[14] As shown in Fig.3, this treatment extends the set of the potential locations for the firms to 15 slots, while maintaining the number of consumers populating the linear city at 7. In other words, demand is unchanged (*i.e.*, 7 consumers), but prior to locating, firms are now uncertain about the locations of the consumers segment, which one may locate between sites -3 and 11.

[13] In a recent paper, Król (2012) examines the case in which firms do not know the exact probability distribution of the mean of the consumer distribution, yielding *ambiguous* consumer demand. Because firms are no more able to compute the expected profits in the location subgame, the author analyzes product differentiation decisions when firms adopt pessimistic decision criteria. The resolution of the game reveals that the optimal strategy consists in adopting an extreme form of pessimism, which leads firms to locate closer together when demand uncertainty increases, a result similar to our theoretical prediction when considering risk-averse firms.

[14] Although Meagher and Zauner (2005) examine higher levels of uncertainty, our choice of $L = 8$ is the result of a delicate tradeoff between finding a sufficiently high level of uncertainty, such that we can observe a change in the equilibrium outcome, and limiting the support of the consumer distribution (*i.e.*, reducing L) to avoid an excessive number of equilibria with a large share of non-buying consumers. A disadvantage when increasing the extent of the uncertainty is that we significantly increase the choice set of locations, thereby complicating the task of the subjects and encouraging them to behave as local monopolists.

In a third treatment, we define a lower level of uncertainty, such that we obtain identical location equilibria with respect to the DC treatment. This last treatment, labeled *Low Demand Uncertainty* (LDU), is conducted by assuming that $L = 4$ which offers 11 locations for firms (see Fig.2; the locations are labeled from -1 to 9). Intuitively, we expect that the level of differentiation expressed by risk-neutral firms in this treatment will not differ from that in the DC case.

Similar to the baseline case, a unique SPE in pure strategy can be characterized by solving these two variants of the game by backward induction. As before, we first determine the price equilibrium for each pair of locations. Then, given the matrix of payoffs for each pair of locations, we derive the unique location equilibrium in pure strategy.[15] As noted above, the location and price equilibria obtained in the LDU treatment are similar to those derived under perfect knowledge about the location of demand.

Proposition 2 *The unique SPE for the location-then-price game under low demand uncertainty and risk neutrality is* $(x^\star_{L1}, x^\star_{L2}) = (2, 6)$ *with equilibrium prices* $(p^\star_{L1}, p^\star_{L2}) = (7, 7)$.

By contrast, the resolution of the game in the HDU treatment leads to a different location equilibrium.

Proposition 3 *The unique SPE for the location-then-price game under high demand uncertainty and risk neutrality is* $(x^\star_{H1}, x^\star_{H2}) = (1, 7)$ *with equilibrium prices* $(p^\star_{H1}, p^\star_{H2}) = (7, 7)$.

When firms face a high level of demand uncertainty, they choose to locate farther away from one another relative to the DC and LDU treatments. We obtain the central result of Meagher and Zauner (2005), which stipulates that demand uncertainty acts as a differentiation force. Above a certain threshold of demand uncertainty, firms are no longer certain to capture a larger share of demand when locating close to the center. Consequently, the firm's best response consists of reducing the intensity of price competition by locating far away from its rival and, thereby, maximizing its profit. However, unlike Meagher and Zauner (2005), we do not observe that firms raise their prices when demand uncertainty increases. This is due to the combination of three factors that make a deviation from the initial price equilibrium unprofitable: (i) the adoption of a linear transportation cost that strengthens price competition, (ii) a discrete framework that introduces threshold effects in firms' actions, and (iii) the choice of a moderately "high" level of demand uncertainty to limit the number of potential locations.[16]

[15] The price equilibrium payoffs and the equilibrium prices for each pair of locations are given in the Online Appendix.

[16] With a quadratic transportation cost, as in Meagher and Zauner (2005), the incentive for firms to raise their prices when moving away from their rival is more pronounced than with a linear formulation. From a consumer perspective, a quadratic transportation cost makes each supplementary unit of distance to travel increasingly expensive compared with a marginal increase in price. Hence, the more firms differentiate, the greater the decrease in the intensity of price competition. This explains why price competition is more intense with a linear transportation cost than with a quadratic one and, consequently, why firms differentiate less.

Following the resolution of the games, the following theoretical prediction can be easily brought to the data.

Testable prediction 1 *A high demand uncertainty acts as a differentiation force.*

2.4. Behavioral Hypotheses

Thus far, our theoretical predictions have been derived under the assumption of risk-neutral firms. However, it is highly likely that a significant share of decision-makers, both in the lab and within firms, are not risk-neutral. For instance, Asplund (2002) cites several reasons to assume that firm managers are rather risk-averse such as non-diversified owners, liquidity constraints, or non-linear tax systems. This leads us to study the theoretical predictions of the location-then-price game when considering risk-averse and risk-lover firms.

In case of the DC treatment, uncertainty arises from the existence of indifferent consumers. With a sharing rule of 1/2, a firm is not certain to be chosen by an indifferent consumer and thus has to form expectations on the total number of consumers it will attract. In the LDU and HDU treatments, a second source of uncertainty comes naturally from the demand location. Both sources of uncertainty may affect location choices and price decisions.

DC treatment Assuming expected utility theory, the expected profit of a firm i is represented by a power CRRA function of the following form:

$$\Pi_i = \frac{(p_i q_i)^{1-r}}{1-r} \tag{3}$$

where r represents the coefficient of relative risk aversion (CRRA). If $r = 0$, we return to the situation with risk-neutral firms, while $r > 0$ and $r < 0$ denote risk-averse and risk-loving behavior, respectively.[17] In the case of indifferent consumers, the expected profit function is:

$$\mathbb{E}\left[\Pi_i\right] = \frac{1}{2}\frac{\left[p_i \overline{q}_i\right]^{1-r} + \left[p_i\left(\overline{q}_i + \widetilde{q}_i\right)\right]^{1-r}}{1-r} \tag{4}$$

with $\overline{q}$ being the safe demand and $\widetilde{q}$ the number of indifferent consumers. Let us illustrate the importance of risk aversion when some consumers are indifferent between the two firms. Assume that firms are located in $(x_1, x_2) = (3, 5)$ and choose to set identical prices equal to 8. These symmetric outcomes lead each firm to be visited by 3 consumers, while 1 consumer is indifferent. Using the expected profit function of Eq.4, it is easy to show that firm 1 has a higher expected profit by deviating unilaterally from the price equilibrium if and only if it is risk averse. Indeed, with a price of 7, firm 1 captures a safe demand of 4 consumers and its expected profit exceeds that obtained with an expected demand of 3.5 and a price equal to 8,

[17] When $r = 1$, $\Pi_i(\cdot) = ln(\cdot)$.

i.e., $\frac{(7\times4)^{1-r}}{1-r} > \frac{1}{2}\frac{(8\times4)^{1-r}+(8\times3)^{1-r}}{1-r}$, $\forall\, r > 0$. The inequality is only reversed for risk-lover firms (*i.e.*, $r < 0$), meaning that in this case the variation in the marginal revenue is significantly higher with an additional consumer than with one fewer.[18]

In what follows, we determine the game equilibria assuming that firms are sufficiently risk-averse ($r = 0.9$) or risk-lover ($r = -0.2$).[19] Similar to the case with risk-neutral firms, we solve the game by backward induction and determine the subgame perfect Nash equilibria under the assumption that firms have the same degree of risk aversion. The SPEs, as well as the associated demands and profits, are reported in Table 2.

Under perfect information about consumer locations (DC treatment), we find the same location equilibrium, irrespective of firms' risk preferences, *i.e.* $(x_1^\star, x_2^\star) = (2, 6)$. Attitudes toward risk only affect price equilibrium. Price competition is softer for risk-lover firms, $(p_1^\star, p_2^\star) = (8, 8)$, whereas risk-averse firms reach the same price equilibrium as risk-neutral firms, $(p_1^\star, p_2^\star) = (7, 7)$. Firms that enjoy taking risk are less reluctant to set high prices and, hence, to increase the risk of losing consumers. When both firms act in this way, they charge the highest possible price that ensures the market coverage. These symmetric price strategies imply that the consumer located at the city center is indifferent between the two firms. Similar to the example above, both firms gain more from securing this consumer than from losing him and, thus, prefer not to deviate from the symmetric price equilibrium.

LDU and HDU Treatments As shown previously, demand uncertainty encourages firms to locate farther away from the demand center because it is no longer guaranteed that a firm will be chosen by a maximum number of consumers when locating at the city center. The result is that firms prefer to differentiate to relax price competition. However for risk-averse firms, the centrifugal force of demand uncertainty is counterbalanced by the desire to secure safe demand even if it leads to strengthened price competition. The propensity of risk-averse firms to locate close to the center will thus depend on the magnitude of each force.

By solving the game by backward induction, we find that risk-averse firms are particularly dragged toward the middle when the level of uncertainty is high (see Panel B of Table 2). This finding is consistent with the prediction of Asplund (2002), who shows that risk aversion makes competition in prices fiercer in the presence of demand uncertainty. Under a low

[18] For the sake of simplicity, in the case of multiple indifferent consumers, we compute the expected profit by considering only the two polar cases, *i.e.*, none or all indifferent consumers visit a firm. For example, for the locations $(x_1, x_2) = (3, 5)$ and prices $(p_1, p_2) = (5, 3)$, firm 1 obtains 0 safe consumers and there are 3 indifferent consumers. In this case, the expected profit of firm 1 is computed as follows: $\frac{1}{2}\frac{(5\times0)^{1-r}+(5\times3)^{1-r}}{1-r}$.

[19] These numerical values correspond to strong risk aversion and risk-loving levels according to the estimation of CRRA coefficients made by Harrison and Rutström (2008) in their methodological survey. If we refer to the elicitation of risk attitudes used in our experiment, we are able to categorize subjects' coefficient of relative risk aversion. Based on the 10 decisions made by a subject, a coefficient equal to $r = -0.2$ corresponds to a switch to the more risky lottery from the fourth decision and a coefficient equal to $r = 0.9$ corresponds to a switch to the more risky lottery from the seventh decision (see Appendix B).

level of uncertainty about consumer locations (LDU treatment), the location equilibrium becomes $(x^{\star}_{L1}, x^{\star}_{L2}) = (3, 6)$[20] and the level of differentiation decreases again under a high level of demand uncertainty (HDU treatment, $(x^{\star}_{H1}, x^{\star}_{H2}) = (3, 5)$). The decrease in differentiation logically leads to fiercer price competition in both treatments relative to the DC treatment. Compared to risk-neutral firms, considering risk aversion intuitively changes both location equilibria and price equilibria. On the one hand, because the expected demand is lower at the boundaries of the support of the city when uncertainty increases, clustering toward the middle allows firms to maximize the expected number of consumers. Even if this location strategy entails lower profits compared to more extreme locations, it is optimal for risk-averse firms to assign greater weights to states of nature that ensure a certain level of demand. On the other hand, the increase in price competition resulting from a lower level of differentiation also allows market coverage in equilibrium.

Proposition 4 *For risk-averse firms, the unique SPE for the location-then-price game is* $(x^{\star}_{L1}, x^{\star}_{L2}) = (2, 5)$ *with equilibrium prices* $(p^{\star}_{L1}, p^{\star}_{L2}) = (6, 6)$ *under low demand uncertainty and* $(x^{\star}_{H1}, x^{\star}_{H2}) = (3, 5)$ *with equilibrium prices* $(p^{\star}_{H1}, p^{\star}_{H2}) = (2, 2)$ *under high demand uncertainty.*

Considering risk-lover firms, both their risk profile and demand uncertainty should encourage them to differentiate more than in the DC treatment. By comparing the game equilibria among treatments, we find that demand uncertainty acts as a differentiation force for risk-lover firms only in the case of a high level of uncertainty (HDU treatment, $(x^{\star}_{H1}, x^{\star}_{H2}) = (1, 6)$; see Panel C of Table 2). The location equilibrium remains the same under a low level of uncertainty (LDU treatment, $(x^{\star}_{L1}, x^{\star}_{L2}) = (2, 6)$). Moving away from the city center is riskier under demand uncertainty because this reduces expected demand. However, for people who like taking risk, this may allow them to obtain a higher expected profit because the gain associated with a draw of the city center close to them outweighs the loss in the case of a draw implying distant consumers. Turning now to the price equilibria, we find lower equilibrium prices under low and high demand uncertainty ($(p^{\star}_{L1}, p^{\star}_{L2}) = (7, 7)$ and $(p^{\star}_{H1}, p^{\star}_{H2}) = (7, 7)$, respectively) than in the DC treatment. While we have seen that risk-lover firms are more inclined to relax price competition under demand certainty, the introduction of demand uncertainty leads firms to strengthen price competition. This counter-intuitive result is explained by the incomplete market coverage that encourages firms to deviate from higher price equilibria to attract isolated consumers.[21]

Proposition 5 *For risk-lover firms, the unique SPE for the location-then-price game is* $(x^{\star}_{L1}, x^{\star}_{L2}) = (2, 6)$ *with equilibrium prices* $(p^{\star}_{L1}, p^{\star}_{L2}) = (7, 7)$ *under low demand uncertainty and* $(x^{\star}_{H1}, x^{\star}_{H2}) = (1, 6)$ *with equilibrium prices* $(p^{\star}_{H1}, p^{\star}_{H2}) = (7, 7)$ *under high demand uncertainty.*

[20] And its symmetric $(x^{\star}_{L1}, x^{\star}_{L2}) = (2, 5)$.

[21] For instance, under a low level of demand uncertainty and given the location equilibrium $(x^{\star}_{L1}, x^{\star}_{L2}) = (2, 6)$, the price equilibrium $(p^{\star}_{L1}, p^{\star}_{L2}) = (7, 7)$ allows for market coverage, while with a price equilibrium $(p_{L1}, p_{L2}) = (8, 8)$, the aggregate demand will be equal to only 6.6.

Table 2: Location and Price Equilibria by Treatment and Risk Attitude

Treatment	Locations	Prices	Demands	Profits
Panel A: Risk-neutral firms				
DC	(2,6)	(7,7)	(3.5,3.5)	(24.5,24.5)
LDU	(2,6)	(7,7)	(3.5,3.5)	(24.5,24.5)
HDU	(1,7)	(7,7)	(3.4,3.4)	(23.7,23.7)
Panel B: Risk-averse firms				
DC	(2,6)	(7,7)	(3.5,3.5)	(13.8,13.8)
LDU	(3,6)	(6,6)	(4,3)	(13.6,13.2)
HDU	(3,5)	(2,2)	(3.5,3.5)	(10.2,10.2)
Panel C: Risk-lover firms				
DC	(2,6)	(8,8)	(3.5,3.5)	(24.5,24.5)
LDU	(2,6)	(7,7)	(3.5,3.5)	(39.6,39.6)
HDU	(1,6)	(7,7)	(3,3.6)	(34.8,41.4)

Note that if we assume more extreme risk preferences (*i.e.*, $r = 0.999$ for risk-averse firms and $r = -1.6$ for risk-lover firms), the effect of demand uncertainty is exacerbated: risk-averse firms locate next to one another $(x^\star_{H1}, x^\star_{H2}) = (3, 4)$ and compete fiercely in prices $(p^\star_{H1}, p^\star_{H2}) = (1, 1)$, whereas risk-lover firms differentiate more $(x^\star_{H1}, x^\star_{H2}) = (1, 7)$ but set similar prices $(p^\star_{H1}, p^\star_{H2}) = (7, 7)$.

Therefore, the theoretical predictions derived when assuming non risk-neutral firms offer the following testable predictions for the location decisions.

Testable prediction 2 *A high level of demand uncertainty acts as an agglomeration force for risk-averse firms.*

Testable prediction 3 *A high level of demand uncertainty acts as a differentiation force for risk-lover firms.*

3. Experimental Design

Our experimental design is intended to test the differentiation force of demand uncertainty while controlling for subjects' risk attitudes. Each experimental session consists of two experiments, and subjects were required to participate in both. The main experiment refers to the discrete location-then-price game presented above, while the second experiment measures subjects' risk aversion using the design proposed by Drichoutis and Lusk (2012). To avoid order effects, half of the sessions featured the opposite experimental order.

Before the game began, subjects were informed that (i) there would be two independent experiments, (ii) money earned in the experiments would depend on their decisions and the decisions of others in their experimental group, and (iii) they would be paid the earnings they accrue in the two experiments. It was made very clear that information about earnings obtained in each experiment would be given only at the very end of the experimental session. We set this condition to reduce the potential spillover effects of earnings from one experiment to the next.

Regarding the location-then-price game, each subject interacts with rival subjects over 30 periods $t = 1, 2, \ldots, 30$.[22] Specifically, the experiment simulates 6 markets of 5 periods each, where a subject is matched with the same rival during the 5 periods of a market but it is paired with a new rival when a new market begins. In our design, we introduce a series of periods during which subjects can only modify their prices, and we take location decisions as given to allow subjects to adapt their equilibrium strategies in the price subgame. This means that in the first period of each market, a subject chooses both his location and his price, while in the remaining 4 periods of the market, the subject competes only in prices. This setup has the advantage of reflecting the long-term decision that a location choice is in real life. By contrast, price changes are deemed less costly and thus can be made more frequently. Specifically, the timing of the decisions in the first period of each market (*i.e.*, $t = 1, 6, 11, 16, 21, 26$) is as follows: first, the two subjects simultaneously choose their location, the rival's location is then revealed and, next, subjects compete simultaneously in prices; finally, each simulated consumer decides whether to buy from the cheapest firm. At the end of the period, each subject learns (i) his demand level, (ii) his profit and (iii) the price of his rival. Therefore, 4 periods of price competition follow. Once the 5 periods have elapsed, a new market begins and subjects are randomly reshuffled, under the constraint that each subject is matched exactly once with the same rival. This stranger matching protocol is common information. To achieve it, we randomly form groups of 6 participants, and the rematching is made inside each group. This stranger design limits end-game effects on both location and price strategies, which enables us to end the experiment with the last period of price competition in the market.[23] Of course, note that consumer locations are left unchanged during the 5 periods of a market, but may vary, in the LDU and HDU treatments, from one market to another according to the random draw of the city center.[24]

Experimental sessions were conducted at the LABEX-EM (CREM-CNRS) institute of the University Rennes 1. The subjects were students with different backgrounds. The experiment was programmed and conducted using the Z-tree software (Fischbacher, 2007). Participants were invited using Orsee (Greiner, 2015). A total of 6 sessions were conducted for each treatment, with 18 participants per session. No subject had previously participated in a similar experiment, and no one participated in more than 1 session, resulting in 324 participants.

To ensure comparability across sessions and treatments, we randomly formed pairings within

[22]The repetition of the game over a finite number of periods does not change the central prediction of subjects differentiating under demand uncertainty.

[23]Note that Barreda-Tarrazona *et al.* (2011)'s experiment ends with a location and price decision to isolate possible end-game effects.

[24]The draws of the city center were made for the first session and replicated in all other experimental sessions.

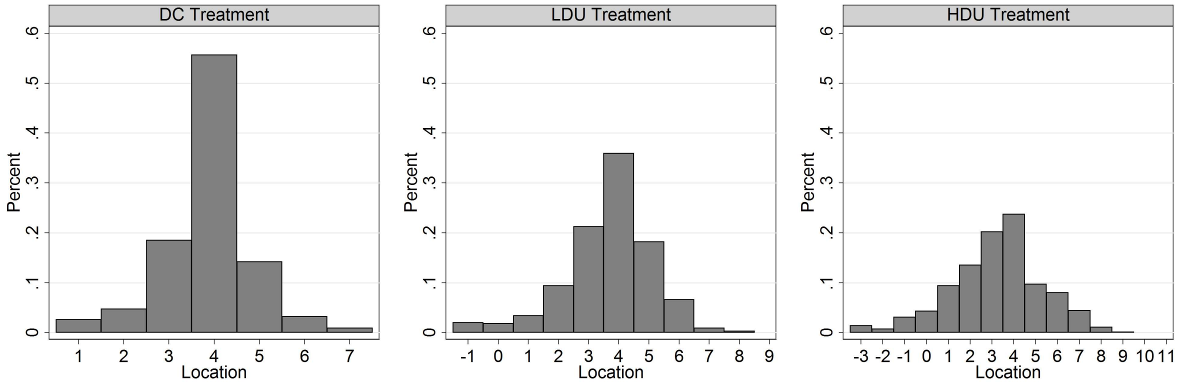
each matching group prior to the first session and used the same pairings in all sessions. Upon arrival, the subjects were randomly seated at visually separated boxes numbered from 1 to 18 in the lab such that neither during nor after the experiment were subjects informed of the identities of the other subjects in the room with whom they were matched. Subjects were then provided written instructions that were read aloud by the experimenter (see the Online Appendix).[25] To ensure that all subjects completely understood the instructions, they were required to calculate firms' profits in hypothetical exercises. Clearly, this may have introduced some bias, but to limit this possibility, the exercises reflect representative contingencies. The responses to these exercises were checked privately before beginning the experiment, ensuring that all subjects completely understood the experiment. Further, a practice round representing 1 market (*i.e.*, 1 period of location then price decisions followed by 4 periods of price decisions) was run before the experiment began.

At the end of the two experiments (*i.e.*, the location-then-price game and the risk experiment), the subjects learned their earnings and then completed a brief post-experimental questionnaire to collect personal characteristics (*e.g.*, age, gender, field of study; see Appendix C). It was made clear from the beginning of the experimental session that their payoff would be equal to their earnings in the two experiments. For the location-then-price game, participants' earnings were proportional to the sum of their profits over the 30 periods. Participants were paid according to the following conversion rate: 25 Experimental Currency Units = 1 euro. The conversion rate was chosen such that, in equilibrium, a risk-neutral subject earned 29.40 euros for the 30 periods in the DC and LDU treatments and 28.47 euros in the HDU treatments, while he could obtain only 4.20 euros for the 30 periods in the DC treatment in case of no differentiation and non-cooperative prices.

In the risk experiment, subjects completed 10 decision tasks. At the end of the experimental session, a decision task was randomly selected for payment, and subjects were paid according to their choice (lottery A or lottery B). The selected decision task was the same for all participants. Subjects knew that at the end of the experimental session, a random device would determine whether they were actually paid. Each subject was given a 1/9 chance of actually receiving the payment associated with his decision. This procedure provided the subjects an incentive to choose according to their true preferences in each decision task, and is thus incentive compatible. Moreover, as Harrison *et al.* (2009) argue, stochastic fees allow one to generate samples that are less risk averse than would otherwise have been observed. The exchange rate used was 0.4 Experimental Currency Units = 1 euro such that the highest earnings equal 11.75 euros. The average length of an experimental session was 80 minutes, and average participant earnings were 17 euros. Further details on the risk experiment are provided in Appendix B.

[25]Note that for simplicity and to facilitate participants' understanding, the demand support is only expressed in positive integers in the instructions.

Figure 4: Location Choices by Treatment



Notes: The graph displays, in each panel, the distribution of location choices for a given treatment.

4. Experimental Results

First, in Section 4.1. we analyze whether subjects differentiate more when demand uncertainty arises. Then in Section 4.2., we examine how demand uncertainty impacts location decisions depending on subjects' risk attitudes. We particularly focus on the results of risk-averse subjects in Section 4.3.. Finally, we examine the relationship between the level of differentiation and prices in Section 4.4..

4.1. Location Choices and Demand Uncertainty

We begin the analysis of the location decisions by pooling all the data. A total of 1944 location decisions were recorded during the 18 sessions. We plot in Fig.4 the location choices for each treatment. A striking result is that the center of the support of the linear city is the most frequent location choice regardless of the level of uncertainty: subjects locate at the center of the demand support in over 55% of all cases in the DC treatment, and the prevalence of the central position is still confirmed in the LDU and HDU treatments, representing 36% and 24% of location choices, respectively. Overall, few subjects decide to settle at the edges of the city. This tendency to cluster in the center is in line with past experimental studies on spatial duopoly markets (*e.g.*,Brown-Kruse *et al.*, 1993; Brown-Kruse and Schenk, 2000; Barreda-Tarrazona *et al.*, 2011).

In Table 3, we report the most frequent pairs of locations observed for each treatment and the average level of differentiation. Clearly, we observe that subjects' location decisions entail less differentiation than those derived from the non-cooperative predictions. This is especially pronounced in the DC treatment, in which subjects of a given market locate simultaneously at the city center (4,4) in more than 32% of the location games, while the second-most preferred location configuration yields only a low level of differentiation. The preferred pairs of locations are thus far away from the non-cooperative location equilibrium $(x_1^\star, x_2^\star) = (2, 6)$. Nevertheless,

Table 3: Summary Statistics on Location Choices by Treatment

Treatment	Modal location	Most frequent pair of locations	Second most frequent pair of locations	% of locations outside $[x_1^\star, x_2^\star]$	Differentiation Mean and S.D.
DC	4	(4,4)	(3,4)	7.08	1.01 (1.02)
LDU	4	(4,4)	(3,4)	16.92	1.54 (1.36)
HDU	4	(4,4)	(3,4)	21.52	2.10 (1.64)

Notes: The percentages reported in the fifth column are defined according to the location equilibrium of the treatment. The location equilibria are (2,6) for the DC and LDU treatments and (1,7) for the HDU treatment. The differentiation is measured by the distance between the two subjects.

we find that the attractiveness of the center decreases when demand uncertainty arises (LDU and HDU). While the pair of locations (4,4) is always the most frequent choice in the LDU and HDU treatments, we observe from the fourth column that subjects are more prone to locate far away from the center in these two treatments. To quantify this pattern, we calculate the percentage of locations outside the range defined by the corresponding location equilibrium $[x_1^\star, x_2^\star]$. For instance, we find that 21.52% of locations are outside this range in the HDU treatment, whereas this concerns only 7.08% of location decisions in the DC treatment. These outcomes arise because subjects are now uncertain of obtaining the maximum demand by locating at the center of the market and prefer moving away from the focal point to lessen competition.

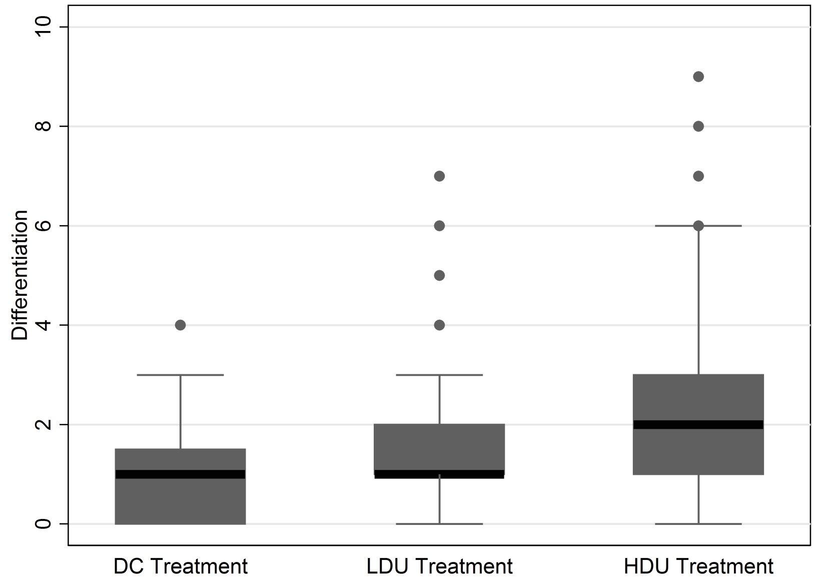
Turning now to the main proposition of the paper, we compare in Fig.5 the distribution of the levels of differentiation obtained in each treatment to verify whether demand uncertainty yields a higher level of differentiation. For each treatment, we have a corresponding Box and Whisker plot that summarizes the distribution of the levels of differentiation computed from all the location games. The differentiation is measured by the distance between the two subjects who compete in a given market. Applying Mann-Whitney U tests, we find that, on average, the differentiation in the HDU treatment is statistically significantly higher than that in both the DC treatment (one-tailed M-W test: p=0.0001) and the LDU treatment (one-tailed M-W test: p=0.0001).[26] In other words, the subjects who faced high demand uncertainty chose to differentiate more. Calculating the average level of differentiation by treatment (see the last column of Table 3), we show that it more than doubles between the DC and HDU treatments. These findings corroborate Testable Prediction 1 and testify to the differentiation force exerted by demand uncertainty.[27] Regarding the literature on (aggregate) demand uncertainty, this result offers a convincing empirical test of the attractiveness of outer locations under demand uncertainty.

Result 1 *Irrespective of risk attitudes, high demand uncertainty yields a higher differentiation than in the case with perfect information about demand location.*

[26] Note that all the results derived in the paper using a Mann-Whitney U test are robust with a Fisher-Pitman test.

[27] Note that, as shown in Appendix B, the shares of the risk profiles are similar among treatments, which rules out any composition effects as an explanation for the observed differences among the treatments.

Figure 5: Level of Differentiation by Treatment



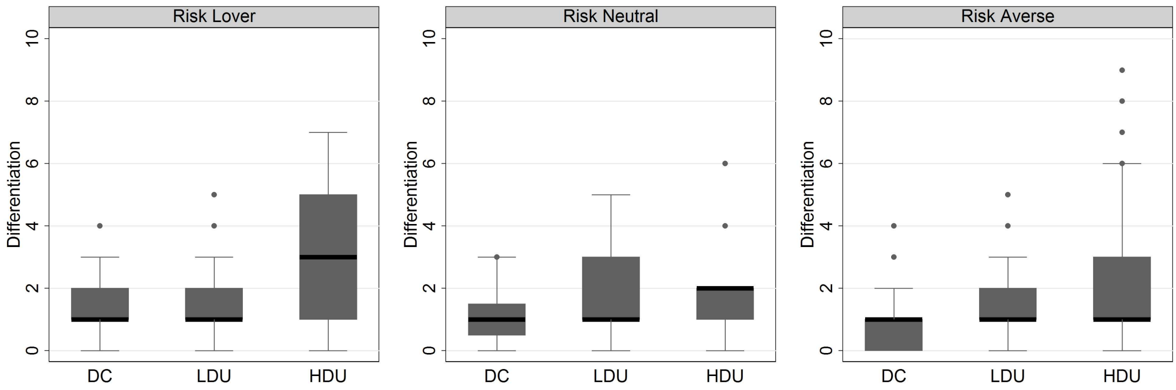
Notes: The distribution of the levels of differentiation for each treatment is represented by means of Box and Whisker plots. The closed boxes are constructed from the first and third quartiles, while the middle bold line indicates the median. The length of the box thus represents the interquartile range (IQR). The whisker lines delimit all observations within 1.5 IQRs of the nearest quartile. Finally, outliers are marked with circles.

Returning to Fig.5, it is noteworthy to mention that we find a significantly higher level of differentiation in the LDU treatment than in the DC treatment (one-tailed M-W test: p=0.0001). Although theoretically a low level of demand uncertainty should not change the level of differentiation, we observe empirically that subjects choose to deviate from the non-cooperative equilibrium, and, thus to differentiate more than in the DC treatment.

4.2. The Effect of Risk Attitudes on Location Choices

Because uncertainty about demand location may have different effects on subjects' location choices depending on their risk attitude, we now analyze how demand uncertainty impacts location decisions for a given risk profile. A preliminary step is to characterize subjects' risk attitudes. Using data from the risk experiment, we are able to provide an estimate of the CRRA for each subject by estimating a structural model of decision-making following the modeling strategy of Harrison and Rutström (2008) and Andersen *et al.* (2010). We then use the CRRA estimates to determine their risk profile. Subjects are either risk-lover, risk-neutral or risk-averse. The classification is achieved by comparing the CRRA estimates with the open CRRA intervals derived from the risk experiment (see Appendix B for further details on the estimation method and the classification). Using this classification, we examine whether demand uncertainty acts as a differentiation force for both risk-lover and risk-neutral subjects, as predicted by the model and whether, by contrast, it drives risk-averse subjects to agglomerate. Because the theoretical predictions have been derived for subjects with identical risk preferences, we concentrate on

Figure 6: Levels of Differentiation by Treatment among Risk Attitude Profiles



Notes: Taking into account only the markets for which subjects and their rival have the same risk profile, we have for risk-lover subjects, 19, 31 and 14 observations; for risk-neutral subjects, we have 20, 18 and 16 observations; and for risk-averse subjects we have 90, 77 and 90 observations for the DC, LDU and HDU treatment, respectively.

markets in which subjects compete with a rival that has the same category of risk attitude.[28] We present in Fig.6 the distributions of the levels of differentiation by treatment and by risk profile.

Is Demand Uncertainty a Differentiation Force? Regarding the first two panels of Fig.6, a first insight is that a high level of demand uncertainty significantly increases the level of differentiation for risk-lover and risk-neutral subjects. On average, the level of differentiation is always higher for the HDU treatment than for the DC treatment, whatever the risk preferences (one-tailed M-W test: risk-lover subjects p=0.0028, risk-neutral subjects p=0.0032). Further, we observe that, on average, the introduction of a low level of demand uncertainty does not induce risk-lover and risk-neutral subjects to differentiate more than in the DC treatment (one-tailed M-W test: risk-lover subjects p=0.3558, risk-neutral subjects p=0.1193). These results are consistent with the Nash equilibria derived from the theoretical model (see Testable Predictions 1 and 3).

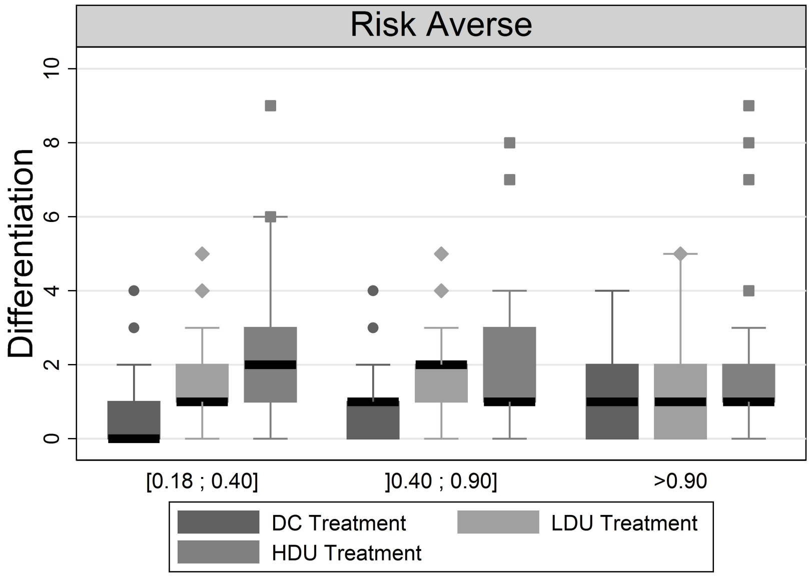
Result 2 *In accordance with the model predictions, a high level of demand uncertainty acts as a differentiation force for both risk-lover and risk-neutral subjects.*

Is Demand Uncertainty an Agglomeration Force? In contrast to the model prediction (see Testable Prediction 2), we observe from the right-hand panel of Fig.6 that risk-averse subjects differentiate more when demand uncertainty arises. On average, the levels of differentiation are significantly higher for both the HDU treatment and the LDU treatment than in the DC treatment (one-tailed M-W test: HDU vs DC p=0.0001, LDU vs DC p=0.0001). We thus do not observe that risk-averse subjects react to demand uncertainty by differentiating less to secure a smaller share of the demand, as predicted by the model.

Result 3 *In contrast to the model prediction, risk-averse subjects differentiate more when demand uncertainty arises.*

[28]By proceeding in this way, we substantially reduce the number of observations used, as shown in Table 8 in Appendix B.

Figure 7: Levels of Differentiation by Treatment and by Subgroup of Risk-Averse Subjects



Notes: The graph displays the distribution of the levels of differentiation by subgroup of risk-averse subjects and by treatment. The subgroups are defined according to the estimated values of the CRRA. In each subgroup, subjects compete with a rival belonging to the same CRRA interval. We count for the first interval 11, 7, and 21 pairs of observations; for the second interval, 8, 12, and 13 pairs of observations; and for the last interval 7, 3, and 6 pairs of observations for the DC, LDU and HDU treatment, respectively.

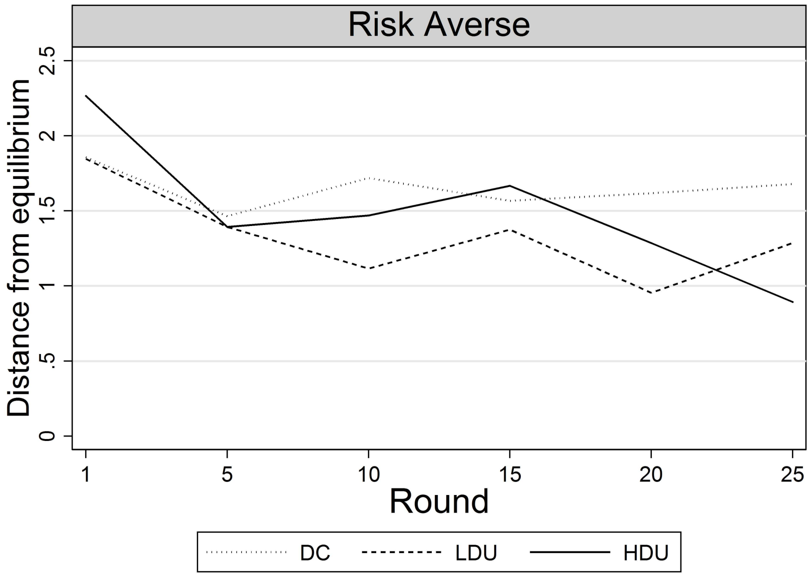
4.3. Explaining Differences for Risk-Averse Subjects

We now investigate possible reasons for the differences between the model predictions and the data for risk-averse subjects.

Heterogeneous Behaviors A first explanation may be that risk-averse subjects behave differently depending on their degree of risk aversion. Our theoretical predictions are derived under the assumption that subjects are highly risk-averse ($r = 0.9$), and it is possible that low and high risk-averse subjects react differently when facing demand uncertainty. This issue is all the more important because we observe sizable heterogeneity in the degree of risk aversion. In particular, low risk-averse subjects account for a large share of the category, as shown in Fig.11 (see Appendix B). To examine the role of individual heterogeneity among risk-averse subjects, we plot in Fig.7 the distribution of the levels of differentiation by treatment and by subgroup of risk-averse subjects. The sample of risk-averse subjects who compete with a rival exhibiting identical risk preferences is decomposed into 3 subgroups according to the estimated value of the CRRA. The decomposition highlights heterogeneous behaviors among subgroups when demand uncertainty increases. In particular, we observe that the more risk-averse subjects are (*i.e.*, high CRRA), the less they differentiate when facing a high level of demand uncertainty.[29] Focusing on high risk-averse subjects (*i.e.*, $r > 0.90$), we find that, on average, the level of

[29]This pattern is confirmed statistically by estimating a Tobit regression, where the level of differentiation between two subjects with the same risk profile is explained by the estimated value of the CRRA and additional covariates. The estimates are reported in Appendix E.

Figure 8: Average Absolute Distance from the Location Equilibrium



Notes: The graph presents the evolution over time of the absolute average distance from the location equilibrium by treatment. The sample is composed of risk-averse subjects who compete with a rival exhibiting identical risk preferences.

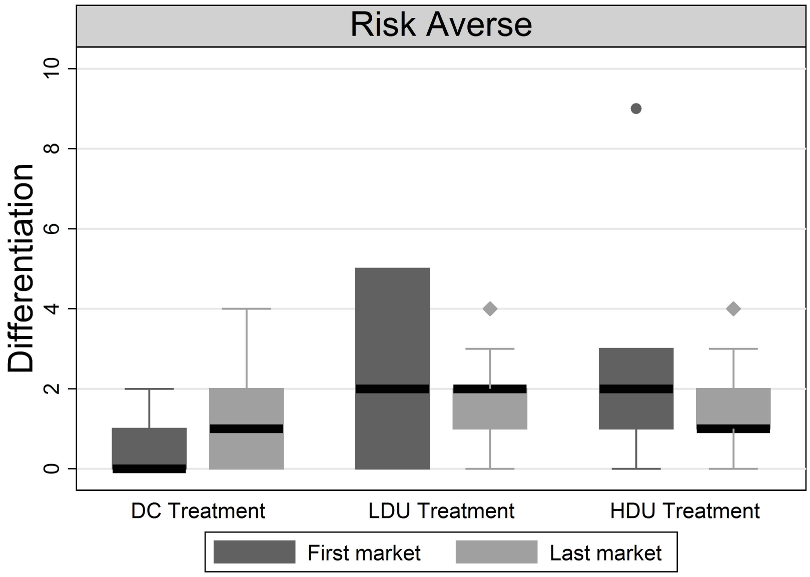
differentiation is identical between the DC treatment and the HDU treatment (two-tailed M-W test: p=0.2520). This means that demand uncertainty acts as a differentiation force only for low risk-averse subjects (one-tailed M-W test: HDU vs DC p=0.0001). When subjects exhibit high risk aversion, the introduction of demand uncertainty does not modify the average level of differentiation: subjects still locate close to the center. It thus appears that risk-averse subjects have heterogeneous behaviors when facing demand uncertainty, and the heterogeneity in the degree of risk aversion explains part of the differentiation force observed.

Learning Effects A second explanation for the differentiation force observed may reside in the existence of learning effects. Despite having implemented a stranger design, subjects may have adapted their location decisions based on their previous decisions. As a consequence, subject's location decisions may evolve over time and eventually converge toward the location equilibrium. To test this hypothesis, we compute the absolute average distance from the location equilibrium resulting from each location choice made by risk-averse subjects in a given market as follows:

$$D = \left(|x_1 - x_1^\star| + |x_2 - x_2^\star|\right)/2 \tag{5}$$

where the location equilibria $(x_1^\star, x_2^\star)$ are those reported in Panel B of Table 2. As before, we conduct our analysis on the sample of risk-averse subjects who compete with a rival exhibiting an identical risk profile. This yields 6 distance measures per subject, *i.e.*, one for each market (round 1, 5, 10, 15, 20, 25). We present in Fig.8 the evolution over time of the absolute average distance from the location equilibrium by treatment. We observe clearly that risk-averse subjects who are confronted with demand uncertainty (LDU and HDU treatments) converge slowly

Figure 9: Levels of Differentiation in the First and Last Market by Treatment



Notes: The graph presents the distribution of the levels of differentiation by treatment in the first and last markets. The sample is composed of risk-averse subjects who compete with a rival exhibiting identical risk preferences.

toward the location equilibrium. The more they play, the closer they come to the location equilibrium. By contrast, no significant learning effect is observed for subjects in the DC treatment. This result suggests that the introduction of demand uncertainty forces risk-averse subjects to more carefully choose their location, and this learning process takes time. Further, the computational effort yielded by demand uncertainty is specific to risk-averse subjects, as we do not observe any such learning process for risk-lover and risk-neutral subjects. Due to the existence of learning effects, we then focus on the last market and examine whether risk-averse subjects still differentiate when demand uncertainty arises. We plot in Fig.9 the distribution of the levels of differentiation by treatment for the first and last markets. It appears now that, in the last market, risk-averse subjects facing demand uncertainty (LDU or HDU treatments) do not differentiate more than subjects in the DC treatment (one-tailed M-W test: HDU vs DC p=0.2780, LDU vs DC p=0.1281). The existence of learning effects is then another explanation for the observed differences between the model prediction and the data.

Result 4 *The heterogeneity in the degree of risk aversion and the existence of learning effects mainly explain the differentiation force of demand uncertainty for risk-averse subjects.*

4.4. Price Competition

Because demand uncertainty is revealed before the price subgame begins, the only source of uncertainty when fixing prices arises from the random allocation of the indifferent consumer(s). It follows that addressing the issue of risk attitudes in the price competition stage is less crucial than before. We thus examine how subjects set prices conditional on their location choices by

Table 4: Differentiation and Price Competition

	All periods of the price games							
Differentiation	%	Average price	S.D.	P25	P50	P75	Equilibrium prices	Distance to demand center
Panel A: DC Treatment								
0	36.73	2.62	1.47	1	2	3	1	0.11
1	38.27	3.44	1.50	2	3	5	(1,2)	0.60
2	16.05	3.90	1.70	3	4	5	(2,6)	1.10
3	5.86	4.39	1.70	3	4	5	(2,7)	1.50
4	3.09	4.67	1.84	3	5	6	(6,7)	2.00
Total	–	**3.31**	**1.66**	**2**	**3**	**4**	–	**0.59**
Panel B: LDU Treatment								
0	23.46	2.38	1.42	1	2	3	1	1.16
1	33.02	2.80	1.34	2	3	4	(1,2)	1.14
2	24.69	3.25	1.46	2	3	4	(1,6)	1.48
3	8.95	3.42	1.66	2	3	5	(2,6)	2.12
4	5.86	3.48	1.61	2	3	5	(3,7)	2.42
5	3.09	3.91	1.65	3	4	5	(4,7)	2.50
6	0.62	3.50	1.85	2	3	5	(5,7)	3.00
7	0.31	3.40	1.71	2	3	4	(5,7)	3.50
Total	–	**2.95**	**1.50**	**2**	**3**	**4**	–	**1.45**
Panel C: HDU Treatment								
0	14.81	2.09	1.31	1	2	3	1	2.48
1	26.85	2.59	1.46	2	2	3	(1,2)	2.56
2	24.38	2.49	1.40	1	2	3	(1,6)	2.78
3	15.12	2.91	1.52	2	3	4	(2,6)	2.50
4	11.73	3.32	1.74	2	3	5	(2,6)	3.24
5	2.78	3.83	2.06	2	4	5	(4,7)	4.06
6	2.47	3.88	1.96	2	4	5	(5,7)	4.13
7	1.23	4.13	1.57	3	4.5	5	(5,7)	4.50
8	0.31	3.50	2.68	1	3	6	(6,7)	5.00
9	0.31	2.40	0.84	2	3	3	(5,7)	4.50
Total	–	**2.71**	**1.58**	**2**	**2**	**4**	–	**2.79**

Notes: The first columns of the table report some summary statistics on prices by level of differentiation and by treatment. The column denoted *Equilibrium prices* reports the minimum and maximum values of equilibrium prices for risk-neutral subjects by differentiation level for each treatment. Finally, the last column presents the average distance between a subject and the demand center.

pooling all the price data, and we refer to the predictions derived for risk-neutral subjects.[30] Further, recall that in the experiment, subjects compete in prices with the same rival during 5 periods. These repeated interactions may lead prices to evolve over time in a given market. The results presented below account for all the periods of the price game, but they are insensitive to examining only at the first or the last period. We refer the reader to Appendix F for a dedicated analysis of the dynamics of price competition.

Differentiation and Price Level One of the appeals of our study is that it allows to investigate the relationship between the level of differentiation and price competition; a subject widely debated in the theoretical literature but too rarely brought to the data. To examine whether high levels of differentiation allow subjects to charge higher prices, we report in Table 4 the

[30]Note, however, that the following results are robust if we conduct the analysis by risk profile.

average prices by level of differentiation. Regarding the DC treatment (Panel A), we confirm that, on average, subjects succeed at relaxing price competition when differentiation increases (Spearman rank correlation coefficient, $\rho = 0.3588$; $p = 0.0001$). This result supports the positive relationship between prices and differentiation, and corroborates the finding of Barreda-Tarrazona *et al.* (2011). However, this result does not hold for the LDU and HDU treatments, in which lower prices are observed for the highest levels of differentiation. In what follows, we explain these findings by comparing the posted prices with the theoretical predictions.

Pricing Behaviors We report in the penultimate column of Table 4 the range of non-cooperative equilibrium prices for each level of differentiation. For all treatments, we find that the average and median prices are in accordance with the non-cooperative equilibria only in the case of intermediate levels of differentiation (*i.e.*, 2, 3 or 4). For other levels of differentiation, two opposite behavioral strategies are observed. When subjects highly differentiate (*i.e.*, above 4), we note that they partially fail to relax price competition by setting prices slightly below the non-cooperative equilibrium. This deviation is explained by the non-optimal coverage of the market. Indeed, under high levels of differentiation, it is more likely that one of the two subjects is farther away from the center of demand, as shown in the last column of Table 4. This, in turn, forces the subject located farthest away to set a low price, which triggers greater price competition. Conversely, for low levels of differentiation (*i.e.*, 0 and 1), we find that the average and median prices are above the range of equilibrium prices. This means that in the case of null or minimal differentiation, subjects attempt to tacitly collude by fixing prices above the non-cooperative equilibrium. Hence, the pro-collusive effect exceeds the pro-competitive effect in the case of minimal differentiation. However, the observed prices are far below the equilibrium prices under collusion, which means that subjects fail to achieve the collusive outcome (see Appendix F).

Result 5 *Only an intermediate level of differentiation leads subjects to set prices compatible with the non-cooperative equilibrium.*

5. Conclusion

Since the end of the past century, the question of how to position a product has become a more crucial issue for firms entering new markets. Due to ever-evolving consumer demand, firms face considerable uncertainty about consumer tastes. In response to this demand uncertainty, multinational firms spend billions of dollars on market research to gather information on consumer preferences and gauge demand before launching a new product.

Recent research on product differentiation predicts that firms would differentiate more when uncertainty increases. The reason is that it is more profitable for firms to differentiate when demand uncertainty arises because price competition is relaxed and losing demand is not guaranteed. In this paper, we empirically test the differentiation force of demand uncertainty by conducting a laboratory experiment in which subjects play the two-stage game of Hotelling (1929)'s model. Demand uncertainty is introduced through a random shift of the city center, and demand location information is only revealed before the price subgame begins. We first derive the theoretical predictions of the discrete location-then-price game for different levels of demand uncertainty and we show that demand uncertainty acts as a differentiation force as in the continuous case. Then, we investigate whether subjects' risk attitudes modify their location and price decisions, and we provide new predictions regarding this issue. In particular, we show that risk-averse subjects react to demand uncertainty by locating closer to the demand center to secure part of the demand, unlike risk-lover and risk-neutral subjects. Our results emphasize the importance of risk attitudes when analyzing the effect of demand uncertainty on differentiation strategies. While this dimension has thus far been neglected, we demonstrate that risk preferences may lead decision-makers to react in opposite ways when facing demand uncertainty.

Our empirical findings demonstrate that demand uncertainty acts as a differentiation force for risk-neutral and risk-lover subjects. These results support the growing literature on product differentiation that includes demand uncertainty and can explain why differentiated products slowly replaced standardized products in emerging markets. From a welfare perspective, this questions the benefits of reducing demand uncertainty through public policies in markets where firms are risk-neutral or risk-lover. Because it has been shown that welfare losses increase with demand uncertainty (see, *e.g.*, Meagher and Zauner, 2004), it could be socially optimal to reduce excess of differentiation by facilitating the acquisition of information about consumer preferences.

However, the experimental data do not validate the prediction that risk-averse subjects will agglomerate more when facing demand uncertainty. We explain this puzzling result by the combination of two different factors. First, we observe important heterogeneity among risk-averse subjects and find that the more risk-averse subjects are, the less they differentiate. Second, the dynamic analysis of the location choices reveals the existence of learning effects, in the sense that risk-averse subjects converge slowly toward the location equilibrium. Accounting for both factors and limiting the analysis to a subsample of the data, we actually find that demand uncertainty leads risk-averse subjects to agglomerate. However, this result is based on few observations and needs to be verified using larger samples in the future.

Regarding the price data, we find that subjects set prices in accordance with the non-cooperative equilibrium only for intermediate levels of differentiation. For low levels of differentiation, they attempt to collude to avoid a fierce price competition, whereas they set prices below the non-cooperative equilibrium for high levels of differentiation due to the non-optimal coverage of the market.

Finally, it would be interesting for future research to relax the assumption of simultaneous location choices and investigate the more realistic case of sequential location choices. In particular, our experimental setting offers an ideal framework to empirically test the prediction that demand uncertainty leads firms to cluster at the demand center when firms locate sequentially and have different levels of information about demand location (see Ridley, 2008; Aiura, 2010, for instance), which is typical of retail markets.

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Appendices

A Price Equilibrium

To determine the subgame perfect Nash equilibria (SPEs) of the location-then-price game, we first derive price equilibria for each pair of locations (x_1, x_2). For a given pair of locations, we compute the firm's demand and the resulting profit for every possible price combination. Then, we determine the Nash equilibrium of each pair of locations. Table 5 reports the equilibrium prices, the firm's demand, and the firm's profit for each pair of locations for the DC treatment under the assumption that firms are risk-neutral. The firms' profits correspond to those reported in Table 1.

To illustrate how we determine a unique price equilibrium in the case of a multiplicity of equilibria, we provide a numerical example in what follows. When several price equilibria exist for a given pair of locations, we select the Pareto price equilibrium. For instance, assume risk-neutral firms and the pair of locations (3,4) in the DC treatment. There are two potential Nash price equilibria. In the first equilibrium, each firm sets a price equal to 1, and the corresponding profits are (3,4). In the second one, each firm sets a price equal to 2, and the corresponding profits are (6,8). The result is that the selected price equilibrium is (2,2), as it is Pareto optimal. When no Pareto price equilibrium exists, we select the joint profit-maximizing equilibrium. Finally, it is noteworthy that a price equilibrium in pure strategies does not exist for each pair of locations. For these particular price-setting games, we thus calculate a mixed-strategies Nash equilibrium by considering all the plausible price supports, that is, all prices that have a positive probability of being played in an equilibrium strategy.

Note that while firms choose their location with perfect knowledge about the location of demand in the DC treatment, it is unknown in the LDU and HDU treatments. The uncertainty about demand location implies several potential demand locations that we assume uniformly distributed in the computation of the expected demand and the resulting expected profit. Otherwise, we proceed in exactly the same way as in the computation of the price Nash equilibria in the three experimental treatments. We report in the Online Appendix the equilibrium prices derived for risk-averse and risk-lover firms in the DC treatment and for risk-averse, risk-neutral and risk-lover firms in the LDU and HDU treatment. We also provide a numerical example in the case of a multiplicity of price equilibria.

Table 5: Equilibrium Prices for Each Pair of Locations and Risk-Neutral Firms (DC Treatment)

Pair of locations	Prices	Demands	Profits
Level of differentiation equal to 0			
(1,1)	(1,1)	(3.5,3.5)	(3.5,3.5)
(2,2)	(1,1)	(3.5,3.5)	(3.5,3.5)
(3,3)	(1,1)	(3.5,3.5)	(3.5,3.5)
(4,4)	(1,1)	(3.5,3.5)	(3.5,3.5)
(5,5)	(1,1)	(3.5,3.5)	(3.5,3.5)
(6,6)	(1,1)	(3.5,3.5)	(3.5,3.5)
(7,7)	(1,1)	(3.5,3.5)	(3.5,3.5)
Level of differentiation equal to 1			
(1,2)	(1,1)	(1,6)	(1,6)
(2,3)	(1,1)	(2,5)	(2,5)
(3,4)	(2,2)	(3,4)	(6,8)
(4,5)	(2,2)	(4,3)	(8,6)
(5,6)	(1,1)	(5,2)	(5,2)
(6,7)	(1,1)	(6,1)	(6,1)
Level of differentiation equal to 2			
(1,3)	([2,3][0.41,0.59],[3,4][0.86,0.14])	(2.92,4.08)	(4.71,15.88)
(2,4)	([2,4,5][0.23,0.12,0.65],[4,5,6][1,0,0])	(2.75,4.25)	(10,17)
(3,5)	([4,5,6][0.11,0.48,0.41],[4,5,6][0.11,0.48,0.41])	(3.5,3.5)	(18.2,18.2)
(4,6)	([4,5,6][1,0,0],[2,4,5][0.23,0.12,0.65])	(4.25,2.75)	(17,10)
(5,7)	([3,4][0.86,0.14],[2,3][0.41,0.59])	(4.08,2.92)	(15.88,4.71)
Level of differentiation equal to 3			
(1,4)	([2,4,5][0.16,0.07,0.76],[5,6,7][1,0,0])	(1.77,5.23)	(10,22.42)
(2,5)	([4,6][0.06,0/94],[6,7][0.33,0.67])	(3.44,3.56)	(20.01,23.65)
(3,6)	([6,7][0.33,0.67],[4,6][0.06,0/94])	(3.56,3.44)	(23.65,20.01)
(4,7)	([5,6,7]1,0,0],[2,4,5][0.16,0.07,0.76])	(5.23,1.77)	(22.42,10)
Level of differentiation equal to 4			
(1,5)	(6,7)	(3,4)	(18,28)
(2,6)	(7,7)	(3.5,3.5)	(24.5,24.5)
(3,7)	(7,6)	(4,3)	(28,18)
Level of differentiation equal to 5			
(1,6)	(7,7)	(3,4)	(21,28)
(2,7)	(7,7)	(4,3)	(28,21)
Level of differentiation equal to 6			
(1,7)	(7,7)	(3.5,3.5)	(24.5,24.5)

Notes: For price equilibria in mixed strategies we report into brackets both the prices and the associated probabilities.

B Risk

2.1. Experimental Design

A wide variety of methods could be used to elicit individuals' risk preferences. In our design, we follow the experiment of Drichoutis and Lusk (2012). Each subject completes 10 decision tasks where each task represents a choice between two binary lotteries, A and B. As shown in Table 6, the probabilities remain constant and equal to 1/2 across the decision tasks and in the lowest payoff for each lottery.

Table 6: Elicitation Task for Risk Preferences

Decision task	Lottery A		Lottery B		Expected payoff difference (A-B)	Open CRRA interval if subject switches to lottery B	
	Prob 0.5	Prob 0.5	Prob 0.5	Prob 0.5			
1	1.68	1.60	2.01	1.00	0.13	$-\infty$	-1.71
2	1.76	1.60	2.17	1.00	0.10	-1.71	-0.95
3	1.84	1.60	2.32	1.00	0.06	-0.95	-0.49
4	1.92	1.60	2.48	1.00	0.02	-0.49	-0.15
5	2.00	1.60	2.65	1.00	-0.03	-0.15	0.14
6	2.08	1.60	2.86	1.00	-0.09	0.14	0.41
7	2.16	1.60	3.14	1.00	-0.19	0.41	0.68
8	2.24	1.60	3.54	1.00	-0.35	0.68	0.97
9	2.32	1.60	4.50	1.00	-0.79	0.97	1.37
10	2.40	1.60	4.70	1.00	-0.85	1.37	$+\infty$

Note: Payoffs are in experimental currency units. The last three columns reporting expected payoff differences and intervals for CRRA estimates were not shown to subjects.

Compared to the well-known Holt and Laury (2002) task, the probabilities remain constant across the 10 decision tasks and the euro payoffs change, such that the switch point from lottery A to lottery B can only be explained by the shape of the utility function and, in turn, risk attitudes. This method has the clear advantage of removing non-linear probability weighting as an explanation for the switch between lottery A and lottery B.

Previous experimental studies have underlined several switching back behaviors from lottery B to lottery A after the first switch. As noted by Andersen *et al.* (2006), it is quite possible that such switching behaviors are the result of the subject being indifferent between lotteries. To limit this behavior and obtain a more precise estimation of risk attitudes, we allow an explicit indifferent option for each pairwise lottery. Although it is possible for them to switch back, they also have the option of explicitly selecting indifference. The decision task is thus presented as follows:

Figure 10: Computer Screen for a Decision Task in the Risk Experiment

Subjects' choices are used to determine their risk preferences. For instance, a risk-neutral subject would choose lottery A for the first five decisions listed in Table 6 because the expected value of lottery A exceeds the expected value of lottery B for the first five choices. As one moves down each row of Table 6, the expected value of lottery B exceeds the expected value of lottery A. Thus, responses to these pairwise lottery choices allow us to estimate the coefficient of relative risk aversion for each subject.

2.2. Structural Estimation of Risk Aversion

We estimate a structural model while assuming expected utility theory. We follow the modeling strategy of Harrison and Rutström (2008) and Andersen *et al.* (2010) to identify risk aversion parameters for the subjects in our sample.

From Table 6, we observe that subjects face a series of lottery choices j, where a choice has to be made between two lotteries A and B: $\{(p_j^A, y_h^A; 1 - p_j^A, y_l^A); (p_j^B, y_h^B; 1 - p_j^B, y_l^B)\}$. Lottery A (resp. B) offers a high outcome y_h^A (resp. y_h^B) with probability $p_j^A = 1/2$ (resp. $p_j^B = 1/2$) and a low outcome y_l^A (resp. y_l^B) with probability $1 - p_j^A = 1/2$ (resp. $1 - p_j^B = 1/2$). Note that lottery B has a larger variance than lottery A. We model individual utility as suggested by expected utility. The value function is written as follows:

$$u(y) = \frac{y^{1-r}}{1-r} \tag{6}$$

where y is the lottery prize and $r \neq 1$ a parameter to be estimated. For $r = 1$, we assume that $u(y) = ln(y)$ if needed. Thus, r is the coefficient of relative risk aversion (CRRA), with $r < 0$, $r = 0$, and $r > 0$ yields a convex, linear or concave value function, respectively, and so risk-lover, risk-neutral or risk-averse subjects.

We model the decision using of a discrete choice model in which we consider a latent variable y^* associated with the decision process. We do not observe y^* but only the choices that subjects make:

$$y = \begin{cases} 1 \text{ if } y^* > 0 \\ 0 \text{ if } y^* \leq 0 \end{cases} \tag{7}$$

It follows that for subject i and for a given lottery $k \in \{A, B\}$, the expected utility is written as:

$$EU_i^k = (p_j^k)u_i(y_h^k) + \left(1 - p_j^k\right) u_i(y_l^k) \tag{8}$$

Finally, we allow subjects to make some errors; that is, the probability of choosing a lottery is not one when the expected utility of that lottery exceeds the expected utility of the other lottery. We consider the Fechner specification popularized by Hey and Orme (1994) that implies a simple change in the difference in expected utility:

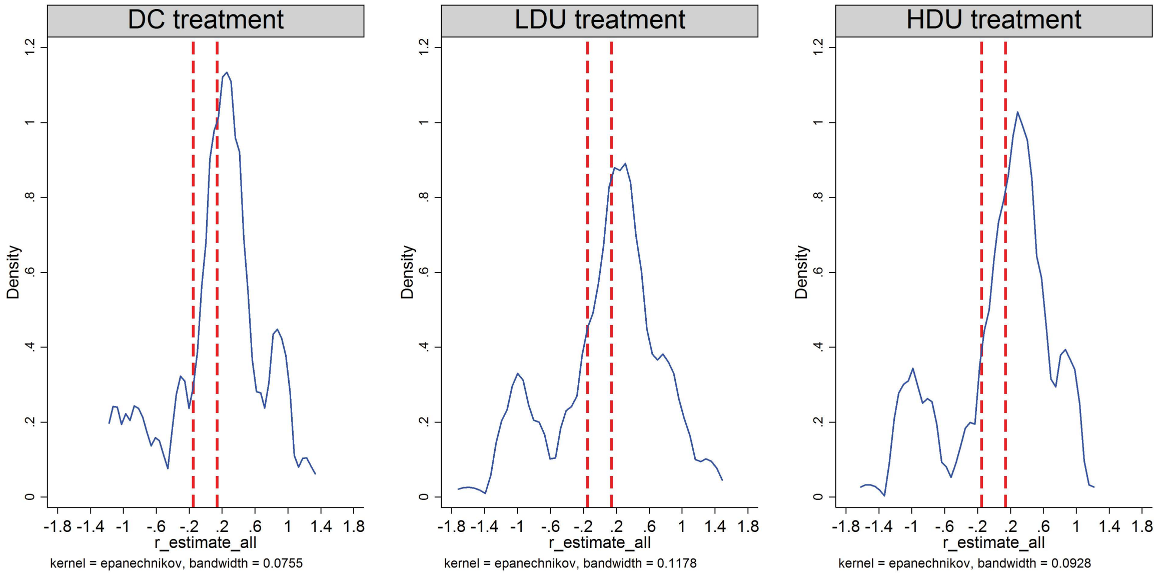
$$\nabla EU = (EU^B - EU^A)/\text{`}noise' \tag{9}$$

We estimate the CRRA for each subject using a maximum likelihood estimator. The log-likelihood function is written as in Eq.10, where $\Phi(\cdot)$ is the standard normal distribution function, $y_i = 1$ when lottery B is chosen, $y_i = -1$ when lottery A is chosen, and ∇EU is the difference in expected utility between the two lotteries.

$$\begin{aligned} ln(L(r, noise:)) \quad = \quad & \sum_i [(\ln \Phi(\nabla EU)|y_i = 1) + (\ln \Phi(1 - \nabla EU)|y_i = -1) \\ & + (ln(1/2\Phi(\nabla EU) + 1/2\Phi(1 - \nabla EU))|y_i = 0)] \end{aligned} \tag{10}$$

The distribution of CRRA estimates obtained in each treatment is plotted in Fig.11.

Figure 11: Estimated CCRA with a Power Function and Fechner Noise



Notes: The dashed lines represent the interval of CRRA values for risk-neutral subjects. Density at the left (resp. right) represents values for risk-lover (resp. risk-averse) subjects.

We observe that the density of CRRA estimates is similar for each experimental treatment (Kruskal Wallis test, $p = 0.3324$). Further, for each treatment, the main part of the density function lies to the right of the risk-neutral prediction, revealing a tendency toward risk-averse behavior among our participants. Using the CRRA estimates and the CRRA intervals reported in Table 6, we are able to determine the risk profile of each subject. The results are reported in Table 7. We note that the frequency of risk-lover, risk-neutral and risk-averse subjects does not differ significantly depending on the experimental treatment. Further, in each treatment, one-half of subjects are risk-averse, and the remaining subjects are almost equally divided between risk-lover and risk-neutral.

Table 7: Share of Risk Attitudes by Treatment (in %)

Treatment	Risk-Lover	Risk-Neutral	Risk-Averse
DC	22.22	25.00	52.78
LDU	26.85	23.15	50.00
HDU	24.07	23.15	52.78

When we analyze whether risk preferences may explain the observed location choices and the resulting levels of differentiation, we restrict our sample to subjects who have the same risk profile as their rival. In this way, we are able to compare the observed locations and the levels of differentiation with our theoretical predictions. From the 324 pairs of locations per treatment, this requires us to restrict our sample of observations as reported in Table 8.

Table 8: Number of Observations when Subjects are Paired with a Rival of Similar Risk Attitude

Treatment	Risk-Lover	Risk-Neutral	Risk-Averse
DC	19	20	90
LDU	31	18	77
HDU	14	16	90

C Additional tables

Table 9 reports some descriptive statistics on subject characteristics.

Table 9: Descriptive Statistics on Subject Characteristics

Variable	DC treatment	LDU treatment	HDU treatment
Age	19.79	20.30	19.96
Woman	0.48	0.53	0.45
Level of study			
Licence 1	0.32	0.34	0.41
Licence 2	0.36	0.27	0.27
Licence 3	0.17	0.22	0.16
Master 1	0.14	0.10	0.07
Master 2	0.00	0.03	0.05
> Master	0.00	0.01	0.00
Other	0.01	0.03	0.04
Field of study			
Economics	0.64	0.59	0.64
Administration, Economics and Social	0.01	0.00	0.02
Management	0.04	0.04	0.06
Law	0.10	0.12	0.11
Political Science	0.01	0.01	0.00
Medicine	0.01	0.03	0.00
Literature	0.01	0.02	0.01
Other	0.18	0.19	0.16
College			
University	0.98	0.94	0.92
Engineering school	0.01	0.01	0.01
Other	0.01	0.05	0.07
Labor activity	0.19	0.23	0.17
Financial assets	0.48	0.43	0.44
# of subjects	108	108	108

Note: Mean of variables are reported.

D Tacit Collusion

Throughout the paper, we have considered competing firms and non-cooperative equilibria. However, a cooperative issue may also exist in the case of colluding firms that seek to maximize their joint profit. Assuming tacit collusion and given that at the beginning of the game firms are identical, no realistic explanations could be given for why their profits should differ at the end of the game. Thus, we restrict our theoretical resolution to the collusive equilibrium that provides equal profits for the two firms. Further, it should be noted that risk attitudes are assumed not to affect the collusive equilibrium in what follows.

Under perfect information about consumer locations, the symmetric joint profit-maximizing solution is obtained for the locations $(x_1^c, x_2^c) = (2, 6)$ and prices $(p_1^c, p_2^c) = (8, 8)$. Expected profit is equal to $3.5 \times 8 = 28$ for each firm, thus yielding a joint profit equal to 56. This expected profit is much lower than that resulting from the subgame perfect Nash equilibrium (49).

The same joint profit-maximizing solution is naturally obtained in the case of low level of demand uncertainty, providing an expected profit for each firm equal to 26.4, instead of 24.5 for the non-cooperative equilibrium of risk-neutral firms.

In these two cases, the location equilibrium for colluding firms corresponds to that of competing firms. Only the price equilibrium change, resulting in an increase in price to maximize the joint profit. The price set at the collusive equilibrium is the highest price that ensures full market coverage.

In the case of high demand uncertainty about consumer locations, the symmetric joint profit-maximizing solution corresponds to the subgame perfect Nash equilibrium (*i.e.*, $(x_{H1}^c, x_{H2}^c) = (1, 7)$ and prices $(p_{H1}^c, p_{H2}^c) = (7, 7)$), providing a joint profit equal to 47.44. Any upward deviation from this price equilibrium leads to a strong decrease in aggregate demand and thus in expected profit. For this collusive equilibrium, the aggregate demand is equal to 6.78. If both firms deviate to a higher price, for instance 8, the aggregate demand falls to 5.55, and this entails a lower expected profit. Moreover, a bilateral deviation to a lower price, for instance 6, allows for full market coverage, but the increase in aggregate demand is insufficient to compensate for the decrease in price to maximize the joint profit. The result is that the symmetric joint profit-maximizing equilibrium is necessarily the non-cooperative one.

E Heterogeneous Behaviors for Non-Risk Neutral Subjects

The behavioral heterogeneity of the CRRA estimates is particularly marked for non-risk neutral subjects due to a wider range of variation than observed for risk-neutral subjects. Consequently, the finding that demand uncertainty leads subjects to differentiate may result from composition effects within these two categories. To test whether these results are robust along the distribution of the CRRA estimates, we perform parametric analyses to assess to what extent the differentiation force varies with the degree of subjects' risk aversion.

We estimate a Tobit model with a lower bound set at 0 to account for the minimum level of differentiation. Specifically, we relate the level of differentiation between two subjects with the same risk profile to the degree of demand uncertainty (binary variables for the DC, LDU, and HDU treatments), the estimated coefficient of relative risk aversion, and interaction terms between these variables. We also control for the order of realization of the risk experiment (risk order), subjects' characteristics (age, gender, work, undergraduate, economics student), and the mean effect of the group of 6 subjects whereby pairs of subjects are matched (matching group), and we introduce period fixed effects.

The estimates of the Tobit models are reported in Table 10 with robust standard errors clustered at the matching group level. As shown, both risk-lover (Column 1) and risk-averse (Column 2) subjects differentiate significantly more on average in the HDU treatment than in the DC treatment. Further, we observe that risk-averse subjects in the LDU treatment differentiate more than in the DC treatment. The estimates of the interaction terms provide new insights. When risk-lover subjects face a high level of uncertainty (Column 1), those who are less risk-lover (high CRRA estimates, *e.g.*, $r = -0.1$) differentiate more than their counterparts (low CRRA estimates, *e.g.*, $r = -0.8$). In other words, the closer they are to the risk-neutral category, the more they behave as a risk-neutral subject who – according to the theoretical predictions – exhibits the highest preference for differentiation when facing a high level of demand uncertainty. By contrast, for risk-averse subjects, we find a negative (linear) effect of the CRRA estimates in the HDU treatment on the level of differentiation (see Column 2). This means that subjects who exhibit strong risk aversion (high values of CRRA, *e.g.*, $r = 0.9$) differentiate less than their counterparts (low values of CRRA, *e.g.*, $r = 0.3$) under a high level of demand uncertainty.

Table 10: Tobit Models

Dependent variable: Level of differentiation		
	Risk-Lover	Risk-Averse
	(1)	(2)
LDU treatment	-1.4935	2.5972***
	(1.0404)	(0.4369)
HDU treatment	1.6913*	4.5024***
	(0.9818)	(0.6073)
LDU treatment × Coef. risk aversion	0.2412	-0.8730
	(0.6418)	(0.5298)
HDU treatment × Coef. risk aversion	2.2623***	-1.5623**
	(0.8595)	(0.7616)
Coef. risk aversion	-0.6177	0.8110*
	(0.5854)	(0.4860)
Risk order	-0.5968	2.4330***
	(0.4061)	(0.4493)
Age	0.0857***	0.0358**
	(0.0177)	(0.0143)
Gender	-0.1632	0.3344**
	(0.1809)	(0.1661)
Work	-1.0545***	-0.2648
	(0.2619)	(0.2253)
Undergraduate	-0.4707*	0.2623
	(0.2775)	(0.1739)
Economics student	-0.5136**	0.0751
	(0.2100)	(0.1740)
σ	1.3292***	1.6042***
	(0.2059)	(0.1550)
Period FE	Yes	Yes
Matching group FE	Yes	Yes
Pseudo-R^2	0.1967	0.1126
Observations	128	514
Left-censored obs.	28	152

Notes: Clustered standard errors (at the group matching level) reported in parentheses.*, **, *** indicate significance at the 10%, 5%, 1% level, respectively.

F Dynamics of Price Competition

Compared to the location subgame in which subjects choose a location once and for all for a given market, subjects compete in prices with the same rival during 5 periods in the price subgame. Therefore, we examine in this section whether repeated interactions allow subjects to adjust up or down their price decisions over time and, if prices evolve, whether this price dynamic may overturn our results.

A first step consists in assessing whether prices evolve over time. To do so, we present in the first two columns of Table 11 the average price per level of differentiation computed both in the first period and in the last period of the price game in a given market for each treatment. It is striking that subjects set significantly higher prices in the first period than in the last period for low and intermediate levels of differentiation (*i.e.*, differentiation levels between 0 and 3), and this result holds whatever the treatment. However, for higher differentiation levels, we find that prices set in the last period are more frequently higher than those posted in the first period.

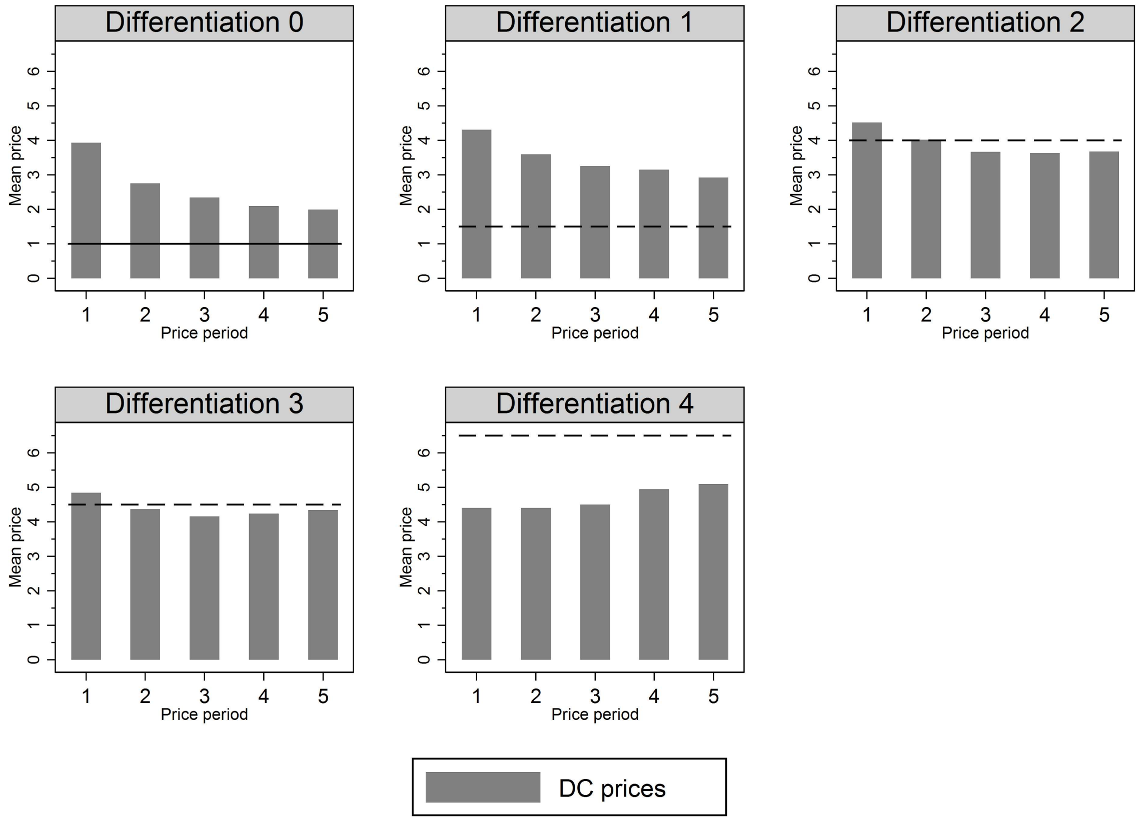
To study these price trends in greater detail, we present in Figs. 12–14 the evolution of the average prices over time for each treatment. The previous findings are confirmed, and we observe that prices significantly decline over time for low and intermediate levels of differentiation. The question is then whether the result that subjects fail to reach the non-cooperative equilibrium predictions and tend to collude at low levels of differentiation remains valid if we only consider the last period of the price games. To answer this question, we first report in Table 11 the range of the non-cooperative and collusive equilibrium prices by level of differentiation for each treatment. We show that considering only the last period of the price subgame does not modify our result: subjects still set prices above the non-cooperative equilibrium predictions at low levels of differentiation whatever the treatment. However, we cannot assert that subjects attempt to collude in prices because the posted prices are far below the collusive equilibrium prices. Nevertheless, if we consider all the price periods, the attempt to collude in prices is clear. As shown in Figs. 12–14, when subjects are located at the same location or next to one another, they attempt to tacitly collude in the first period by setting prices significantly higher than the non-cooperative predictions. However, by failing to achieve the collusive outcome, the low level of differentiation forces them to gradually reduce their prices in the following periods, and subjects face fiercer price competition in the last periods. Furthermore, the consequence of an insufficient level of differentiation for prices is also evident at intermediate levels of differentiation (*i.e.*, differentiation levels 2 and 3). When subjects do not differentiate sufficiently, they fail to sustain high prices throughout the periods, and they are trapped in a price war. This pattern is particularly marked for the LDU and HDU treatments, in which the level of differentiation in equilibrium is higher.

Table 11: Price Decisions at the Beginning and at the End of the Price Competition

	Average price		Equilibrium prices	
Differentiation	First period	Last period	Non-cooperative	Collusive
Panel A: DC Treatment				
0	3.92	1.98	1	(5,7)
1	4.31	2.92	(1,2)	([3,4],[8,9])
2	4.52	3.67	(2,6)	([8],[10])
3	4.84	4.34	(2,7)	([9],[10])
4	4.40	5.1	(6,7)	([8],[10])
Panel B: LDU Treatment				
0	3.65	1.66	1	(4,7)
1	3.73	2.27	(1,2)	10
2	3.95	2.99	(1,6)	8
3	4.09	3.41	(2,6)	([2,5])
4	3.42	3.63	(3,7)	([6,9],8)
5	4.15	3.65	(4,7)	([1,6])
6	3.50	3.50	(5,7)	7
7	4.50	2.50	(5,7)	([6,8])
Panel C: HDU Treatment				
0	3.24	1.51	1	(4,6)
1	3.47	2.04	(1,2)	10
2	3.32	2.06	(1,6)	7
3	3.41	2.69	(2,6)	(6,8)
4	3.50	3.39	(2,6)	([6,9],8)
5	3.78	4.05	(4,7)	([3,7])
6	3.56	3.81	(5,7)	7
7	3.87	4.12	(5,7)	([2,5])
8	3.00	3.5	(6,7)	7
9	1.50	3	(5,7)	([2,5])

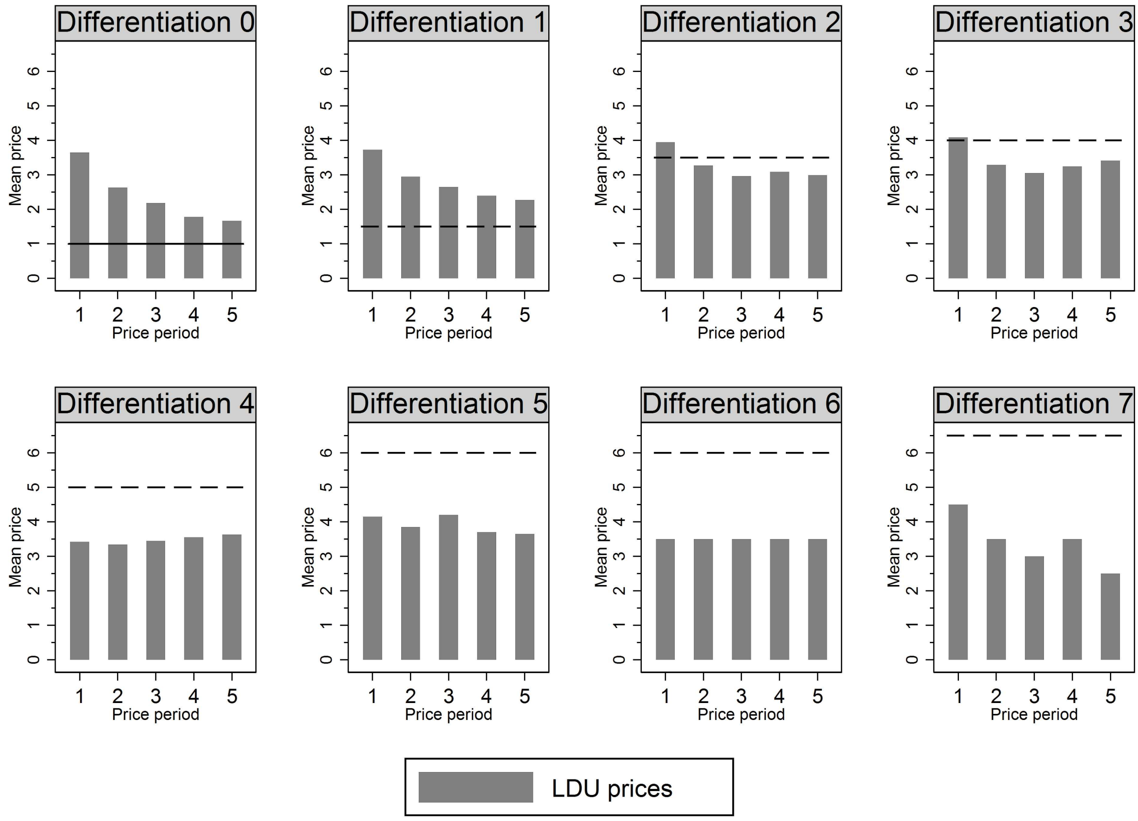
Notes: The columns denoted *Equilibrium prices* report the minimum and maximum values for risk-neutral firms by differentiation level for each treatment.

Figure 12: Evolution of Prices During the 5 Periods of the Price Subgame in the DC Treatment



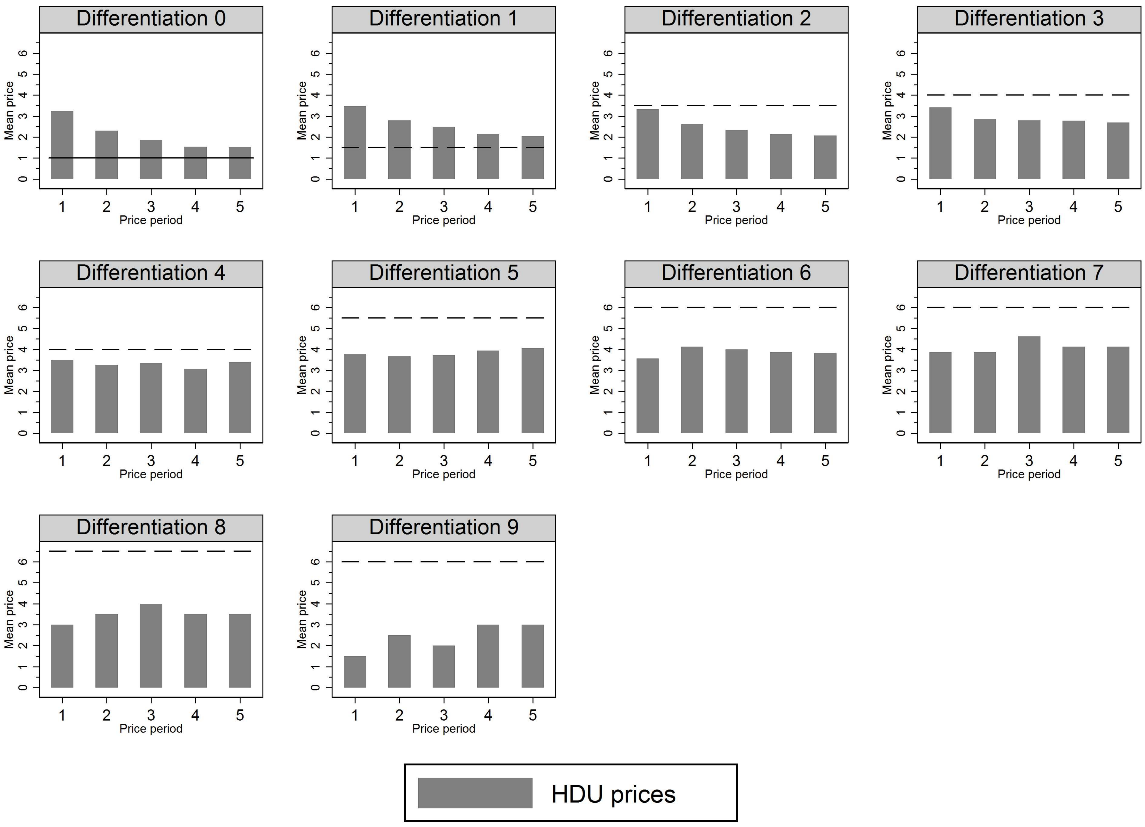
Notes: The graph displays in each panel the mean price set by time period for a given level of differentiation in the DC treatment. A solid horizontal line represents the unique equilibrium price for all the pairs of locations. A dashed horizontal line represents the average of multiple equilibrium prices in the case of mixed strategy equilibria and multiple pure strategy equilibria.

Figure 13: Evolution of Prices During the 5 Periods of the Price Subgame in the LDU Treatment



Notes: The graph displays in each panel the mean price set by time period for a given level of differentiation in the LDU treatment. A solid horizontal line represents the unique equilibrium price for all the pairs of locations. A dashed horizontal line represents the average of multiple equilibrium prices in the case of mixed strategy equilibria and multiple pure strategy equilibria.

Figure 14: Evolution of Prices During the 5 Periods of the Price Subgame in the HDU Treatment



Notes: The graph displays in each panel the mean price set by time period for a given level of differentiation in the HDU treatment. A solid horizontal line represents the unique equilibrium price for all the pairs of locations. A dashed horizontal line represents the average of multiple equilibrium prices in the case of mixed strategy equilibria and multiple pure strategy equilibria.

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