Does Product Complexity Matter for Competition in Experimental Markets?

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Abstract: We describe a first experiment on whether product complexity affects competition and consumers in retail markets. We are unable to detect a significant effect of product complexity on prices, except insofar as the demand elasticity for complex products is higher. However, there is qualified evidence that complex products have the potential to induce consumers to buy more than they would otherwise. In this sense, consumer exploitability in quantities cannot be ruled out. We also find evidence for shaping effects: consumers' preferences are shaped by past experience with prices, and firms may in principle exploit this to sell more.
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1. Introduction

This paper presents a first experimental study of whether product complexity matters for competition and consumers and of whether it should matter for competition and consumer policy. It is often said that consumers are confused by the complexity of products such as modern cars (Rouse, 2008), broadband (Kerven, 2001), electronic products (Bostrom, 2005) and financial services (Hughes, 2007). In the words of an IDC consumer market analyst (reported in Bostrom, 2005), "imagine replacing your TV… today it's digital or analog; 4:3 versus 16:9; direct view, rear projection or a flat. If you go for a flat: a plasma or an LCD? And the resolution: standard, enhanced, or high definition?" Along analogous lines, due to the different combinations of product features and add-ons, the president of a consulting company who conducted a marketing study in the Phoenix area has noted that "an apple-to-apple comparison of multichannel entertainment and related products… is challenging at best and often nearly impossible for the consumer" (cited in Kerven, 2001). Similarly, modern mobile phones have a large number of features the combination of which provides some level of utility to consumers: as a result, in buying a mobile phone, consumers need to reason in terms of expected utility and distribution of possible utility values from buying a particular model of mobile phone. As the number of possible outcomes grows, so does the computational complexity for consumers of figuring out what value they should attach to a given mobile phone, and so does the likelihood that they may be confused, exploited or at least exploitable by firms. A recent report by the U.K. Office of Fair Trading notes that the complexity of decisions may affect consumer choices and that as a result "firms may have an incentive to make consumer tasks more difficult" (Garrod et al., 2008, p. 56). This *consumer exploitation effect* is an example of what marketing research calls 'confusion marketing' (Dacko, 2008, p. 113) and has been modeled by Spiegler (2006). It may lead to higher prices and higher quantities being bought than those that the consumers would buy were they able to exactly identify the value of each product in advance. It can be considered connected to other potential forms of consumer exploitation, such as engaging in complicated descriptions of products (Ellison and Ellison, 2004) or in complicated tariff structures, such as those observed in the U.K. retail electricity market (Wilson and Waddams Price, 2007).

It could, however, also be that consumers react to complexity by being less willing to buy. It is known that subjects in experiments dislike ambiguity in outcomes (Camerer, 1995), and Sarin and Weber (1993) found evidence that ambiguity aversion replicates in market settings. Complexity may be considered related to ambiguity insofar as the inability by the consumer to understand the value of a complex product induces ambiguity in the decision setting. Sonsino et al. (2002) found that, when faced with a choice between a simple and a complex product, in the form of a lottery, subjects tended to prefer the simple product. Their interpretation is that subjects are complexity averse. While this *complexity aversion effect* has been replicated in other individual choice experiments (Huck and Weiszacker, 1999; Sonsino and Mandelbaum, 2001), it has never been tested in a market setting, which is of course the one most relevant for consumer decisions.[1]

It is an open empirical question, therefore, whether a *net* consumer exploitation effect or the complexity aversion effect dominates in the presence of complex products, and if there is a sense in which consumers are more exploitable in the presence of complex products. A net consumer exploitation effect, or at the least the concrete possibility of consumer exploitability, would suggest scope for consumer and competition watchdogs such as the Office of Fair Trading to take product complexity into account in their investigations. Conversely the role of product complexity would seem to be overstated if we find no net evidence of any effect or evidence of a net complexity aversion effect. Thus, our question has policy relevance.

An additional reason why we might expect markets for simple products and markets for complex products to differ is in the elasticity of demand. We would expect markets for

[1] One implication of complexity aversion is that firms may find optimal to *simplify* products. An example of this may be the success of the mono sound and as simple as it gets Tivoli Model One radio (see Triano, 2001, for a review).

complex products to have a more elastic demand than markets for simple products. The reason is straightforward: if consumers have less to rely on because information about the quality features of the product is fuzzy, then they are more likely to rely on the piece of unequivocal information which is available, namely that on prices.

A final motivation of this paper is to look at whether, if consumers see a sequence of prices, their willingness to buy is a function of past prices. It has been argued that agents have unclear preferences and so their willingness to buy may be affected by anchors provided either artificially or through the operation of auction mechanisms (Ariely et al., 2003, 2006; Loomes et al., 2003). Following Loomes et al. (2003), we label these psychological mechanisms *shaping effects*. We hypothesize and test the prediction that, if buyers have experienced lower prices for a given product, they may believe that the value of the product is low and as a result they may be less willing to buy the product. If this is true, consistently pricing high is then a better strategy for firms to try to exploit consumers' uncertainty about their preferences than following a strategy with more variability in terms of mix of low and high prices.

An experimental methodology is especially useful to address these topics for two reasons. First, finding a metric for product complexity is difficult in comparing products that change over a variety of dimensions, whereas in the experimental laboratory we can precisely and unequivocally identify which product is more complex than another, and provide evidence that they are considered such based on the behavior of subjects (namely, their response time in making decisions, which we measure). We rely on the methodology by Sonsino et al. (2002) to identify separate products, in the form of lotteries in keeping with the existing research we are benchmarking our work against. These products are differentiated in complexity by a procedure that multiplies outcomes and scrambles the order they are presented in. Second, a key way product complexity is achieved in retail markets is by adding product features complicating the set of possible utility outcomes, but product features often are themselves a source of utility for consumers, and may also be a source of strategically useful horizontal product differentiation. In the same way in which in an economic model we can investigate the role of a given economic factor by controlling for other factors, in the experimental laboratory we can control for potential confounds and try to isolate a net complexity exploitation (or exploitability, or complexity aversion) effect, if such an alleged effect does exist, independently of additional factors such as the tastes of consumers or inter-firm rivalry. Controlling for the tastes of consumers is the other and more important reason (apart from comparability with the existing experimental literature) for which the choice of lotteries as products is useful in a first experiment on this topic, while we control for inter-firm rivalry by having a single seller. Achieving this can also enable us to more clearly identify eventual shaping effects.

To anticipate our key results, we find no significant evidence of a net complexity aversion effect, while there is evidence of shaping effects and qualified support for potential consumer exploitability if sellers play a consistent intertemporal strategy in choosing prices. Section 2 describes the experimental design, section 3 presents the results and section 4 concludes.

2. Experimental Design

2.1 Products Employed

As discussed in the introduction, we largely modeled our procedure to identify pairs of (simple, complex) products on Sonsino et al. (2002). In brief, the procedure is based on deriving compound lotteries (products) from simple lotteries (products) using small payoff perturbations in a sense detailed below, and on presenting the resulting compound products using a scrambled order format. The procedure enables large changes in product complexity – due to the additional outcomes (27 rather than 3) combined with order scrambling – while making the riskiness of the products indistinguishable, and therefore controlling as much as possible for differences in preferences between products for reasons other than complexity.

Define $p_i > 0$ and $\sum p_i = 1$ as the probabilities attached to outcomes x_i. The simple lotteries, or products, L_{sj} have three possible outcomes and associated probabilities:

$$L_{sj} = (p_1, x_1; p_2, x_2; p_3, x_3)$$

We used two such lotteries (S1 and S2) as products in the experiment (Table 1).

(Insert Table 1 about here.)

Complex products can then be generated by deriving, for any given L_{sj}, a compound lottery L_{cj} that assigns weights α, β and (1 - α - β) to the outcomes of 3 draws of L_{sj}. That is,

$$L_{cj} : L_{cj} = \alpha\, L_{sj} + \beta\, L_{sj} + (1 - \alpha - \beta)\, L_{sj}$$

which is to say that each complex product L_{cj} can be obtained by making three draws of L_{sj}, assigning weights α, β and (1 - α - β) to the outcomes of each draw, and summing up the three weighted payoffs to obtain the L_{cj} payoffs structure. To make a simple example, if L_{sj} were just a flip of a coin with 50% chance of getting 12 pounds (x_1) and 50% of getting 0 (x_2.+ x_3), and if α = β = 1/3, then L_{cj} would correspond to the compound lottery obtained by flipping the coin three times with a 50% chance of getting 4 pounds each time.

Generally speaking, L_{cj} has 3 × 3 × 3 = 27 possible outcomes, and, although in principle some outcomes may yield the same payoff and so may not be separable, the simple products we chose were such that this did not occur in practice, and so there were 27 differentiated outcomes in the complex product (as opposed to the 3 of simple products). While the procedure might in principle mean that L_{cj} is perceived as having a different degree of riskiness relative to L_{sj}, this potential problem can be addressed (a) by choosing α and β small enough as to imply just a small payoff perturbation while still multiplying the number of outcomes; in our experiment, we chose α = 0.03 and β = 0.07, and so our products were defined as follows

$$L_{cj} = 0.03\, L_{sj} + 0.07\, L_{sj} + 0.9\, L_{sj}$$

and, (b) as in Sonsino et al. (2002), by scrambling the order of presentation of the 27 outcomes (see Table 2),[2] thus further helping make the products undistinguishable to the buyers in terms of risk while at the same time being markedly different in terms of complexity.[3] Complex products C1 and C2, derived in this way respectively from S1 and S2, are presented in Tables 3 and 4.

(Insert Table 2 about here.)

2.2 Experimental Structure and Implementation

We ran two experiments: a posted offer market experiment with three treatments (Experiment 1) and an individual choice experiment with two treatments and with a posted offer market frame (Experiment 2). A posted offer market setup corresponds to the reality of retail markets where sellers post prices and buyers simply decide whether and how much to buy at the given price. Both experiments involved the same two pairs of products (S1 and C1 *or* S2 and C2), two trial periods using an example product and four phases; each phase had 10 independent trading periods.

In Experiment 1 subjects were randomly assigned to the role either of seller or buyer while in Experiment 2 all subjects were buyers. They were handed instructions, questionnaires and consent forms. After they read the instructions they answered the questionnaire and if they had any doubts they could ask for clarification. When all the participants were ready, after they did the two trial periods, the experiment started. In the trial

[2] That is, outcomes were not presented from lowest to highest (or vice versa) but instead in a random order.
[3] This is confirmed by the fact that we did not receive any debriefing feedback suggesting that subjects perceived products different in terms of risk. A by-product of our procedure, also entailing additional complexity, was that, while the outcomes and probabilities were integer (or integer percentage) numbers in the simple lotteries, they were figures with up to two decimals in the complex lotteries.

periods we employed an example product, which was the same across sessions and is available in the online instructions. The reason why we used an example product is two-fold. Firstly, we did not want to disclose any information regarding both lotteries. Secondly, we wanted to avoid any possible anchoring effect to the outcomes occurred in the trial phase that could have affected buyers' decisions. In both experiments we used 'points' as the experimental currency (the conversion rate being 975 points to one pound).

Experiment 1 involved 3 treatments: B (Baseline), IS1 (Informed Seller with one product on sale) and IS2 (Informed Seller with two products on sale simultaneously).

The B Treatment. B is the baseline treatment and involved a posted offer market with 1 seller and 4 buyers. The roles did not change throughout the session. In each period only one product was on sale: in phases 1 and 2 the simple lottery and in phases 3 and 4 the complex product in half of the sessions, or vice versa in the other half.

The seller had to state each period the price and the quantity at which he or she was willing to sell the product. The price but not the quantity was shown to the buyers. Buyers had to state the amount of the products they wished to buy, if any, at that price. The order in which they bought was random and determined after they had stated the number of units they wish to buy. It might therefore happen that some buyers did not have the chance to buy what they wanted if they were not the first to buy and the seller had run out of stock.

Using standard experimental methodology (e.g., Davis and Holt, 1993), sellers were given a marginal cost function for each unit they sold (see Table 3). Their profits each period were given by the difference between revenue and cost, and cumulated across the 40 periods to give the final earnings. For experimental simplicity, sellers only produced and so paid costs over units they sold.

(*Insert Table 3 about here*.)

Buyers were given an endowment of 390 points every period that they could use to buy units of the product on sale, each corresponding to one of the lotteries displayed in Table 1 and 2, which had an expected value of 60 points each (though they were not told this). The unspent points were accumulated and part of the final earnings calculated at the end of the session. The bought units of the product were accumulated over the periods. At the end of the session there was a single draw of the simple lottery and of the complex lottery determining the final value of all the units of the simple product and of the complex product held by buyers. Buyers were paid these earnings plus those from unspent points.

The IS1 Treatment. IS1 differed from B in that sellers were more informed. The rationale for this is that we wanted to reduce the likelihood that experimental subjects playing the role of sellers would be confused by the complex products in the same way as buyers might. After all, in the real world, while it is plausible to assume that consumers may be confused, companies do know well the products they sell and they may well be aware of the possible strategic implications of this. Sellers were given six extra initial practice periods in the role of buyer, to give them the flavor of what is like to be in buyers' shoes. They were provided a products sheet containing the products in unscrambled order, unlike the way they were presented on the screen. Finally, they were neutrally provided information on possible complexity aversion and complexity exploitation effects as factors working in opposite directions the relevance or irrelevance of which was for them to decide, stressing that it was up to them to decide whether either, both or neither was worth taking into account.[4]

The IS2 Treatment. IS2 treatment was the same as the IS1 treatment but for one difference: each period both products (S1 and C1 *or* S2 and C2) were on sale simultaneously. Production costs were computed over all the overall amounts produced by sellers in any given period, i.e. as a function of the sum of the units of both the simple and of the complex product sold.

[4] See the experimental instructions in the online appendix for the exact phrasing. Care is required in cases such as this to avoid distorting the results (Zizzo, 2008). The frame was neutral, only provided as suggestions for subjects to take into account or not as they found best, and symmetrical between the two effects working in opposite directions.

Experiment 2. The key difference relative to Experiment 1 was that this was an individual choice experiment. Since there was not a seller, prices were randomly generated from a uniform distribution. Half of the subjects faced high prices ranging between 75 and 95, the other half faced low prices ranging from 45 to 65.[5] Subjects knew that prices were randomly generated, but they knew neither the range of the distribution nor that the distribution was uniform. Buyers could buy any quantity they desired at the stated price. Experiment 2 involved two treatments: IC1 (Individual Choice with one product on sale each period) and IC2 (Individual Choice with two products on sale simultaneously).

The IC1 treatment was an individual choice treatment with only one product on sale each period. As in the B and IS1 treatments, subjects faced either the simple product in phases 1 and 2 and the complex product in phases 3 and 4 or vice versa.

The IC2 treatment was an individual choice treatment with both products (S1 and C1 *or* S2 and C2) on sale throughout the session. As such, it was the counterpart of the IS2 treatment.

3 Experimental Results

The experiments were run at the University of East Anglia between July 2007 and March 2008. Two hundred and sixty eight subjects (mainly students) were recruited via email, and Table 4 contains details on number of subjects and independent observations for each treatment (there were at least 12 in each case). The average earnings were £ 16.01 for around one hour and a half of work. Table 5 reports descriptive statistics on key variables.[6]

(*Insert Tables 4 and 5 about here*.)

Response times of buyers and sellers, i.e. the times it takes them to make decisions, are useful as a validation exercise that complex products were indeed perceived as more complex

[5] The choice of range was decided after observing the average market price in several session we had already run from Experiment 1. The average observed price was 70 and we wanted to discriminate between high and low prices relative to the empirical benchmark.

[6] We analysed, but could not find, any significant difference between each pair of products (S1 and C1 vs. S2 and C2).

by buyers. This can be determined by looking at the treatments where a single product was sold at a time (i.e., B, IS1 and IC1). Table 5 shows that buyers spent approximately 20% of more time in dealing with complex products than in dealing with simple ones. The difference is statistically significant in a Wilcoxon test (p = 0.03).[7] In contrast, there is no statistically significant difference for sellers, and, as shown by Table 5, this is due to the fact that, when sellers were provided with additional information and training (IS1), they spent virtually the same amount of time on choosing prices for both products.

RESULT 1. On average buyers, but not sellers (especially when informed), took more time making decisions in relation to complex products than they did in relation to simple products.

Prices as shown in Table 5 are only of course meaningful for Experiment 1, since in Experiment 2 they were randomly chosen by the computer as discussed in section 2. In Experiment 1 mean prices remain however fairly close in the three treatments, in the 65-70 range, with the mean price of the complex product being slightly higher but not statistically significantly so in Mann Whitney tests either run in relation to the average price across all periods or in relation simply to the average price in the first half of the experiment, in relation to which Figure 1 suggests a short run complexity aversion effect might be present.

RESULT 2. There is no evidence of a net complexity exploitation effect in prices and there is insufficient evidence for a complexity aversion effect in prices, which, if applicable, would only be small and short run.

As Figure 1 shows, there is a small tendency for prices of the simple product to become lower with time (Spearman $\rho = -0.037$, p = 0.039),[8] but even towards the end of the experiment they are above the competitive price of 60. Since ours is a monopoly market, the

[7] As we would expect, response times generally decline as the experiment progresses, though in the B, IS1 and IC1 treatments they spike up in round 21 when a new product is sold.
[8] In relation to the complex product, instead Spearman ρ = -0.012 (p = 0.51).

presence of some market power is to be expected and shows an understanding on the part of sellers of how markets operate.

(*Insert Figure 1 about here*.)

Similarly, if buyers and sellers have an understanding of how the market operates, we would expect a negative relationship between quantity and prices. Figure 2 shows that such a negative relationship exists in relation to both simple products and complex products.

(*Insert Figure 2 about here*.)

A computation of elasticity coefficients shows that demand for simple products is unit elastic (- 0.99, S.E. = 0.05), whereas the demand elasticity coefficient for complex products is – 1.33 (S.E. = 0.06). As predicted, buyers are more sensitive to changes in prices in the case of complex products than in the case of simple products.

RESULT 3. Buyers and sellers show a basic understanding of the experimental setup, as revealed by the existence of some monopoly power and of a negative relationship between quantities and prices. Market demand is more elastic for complex products than it is for simple products.

Table 5 shows a small discrepancy between quantities bought and quantities demanded in the case of Experiment 1. This is due to the fact that, while in the individual choice setting of Experiment 2, in Experiment 1 rationing is possible since not enough units may be available at the posted price to cover all the demand.

Table 5 also shows that the picture with quantities is mixed, with quantities demanded and bought sometimes lower and sometimes higher depending on the treatment. Figure 3 illustrates this in relation to quantities bought. In the B treatment there is a marginally statistically significant effect in the direction of net complexity aversion when one looks at quantities bought (Wilcoxon p = 0.08), but this is an artifact of rationing as quantities demanded are virtually the same.[9] The only treatment where there is a genuinely statistically significant effect is in the IC2 treatment, and it is in the direction of a net complexity exploitation effect, with quantities demanded of the complex product being around 15% above those of the simple product (Wilcoxon $p = 0.05$). If we pool IC1 and IC2 treatments, we get suggestive evidence of greater quantity demanded of the complex product in both treatments as a whole (Wilcoxon = 0.08). Similar results are obtained if one looks at expenditures.

(*Insert Figure 3 about here*.)

One problem in interpreting these results is the univariate nature of the statistical tests. It is possible that a net complexity aversion or complexity exploitation effect can be identified, or identified more clearly, once one controls for additional factors. We employed random effects regression models to do this,[10] controlling for the non independence of observations within each market session.

Table 6 presents the estimates of four regression models. Two have the (average) quantity bought each period, whereas the other three have the (average) quantity demanded each period as the dependent variable. The models also differ in the proxy we use for past prices.[11] The reason why these may be important is because of the shaping effects we mentioned as possible in the introduction: subjects' preferences may be shaped by past prices (e.g., Loomes et al., 2003). Depending on the regression model, we use one of two proxies for shaping: lagged average price (LagAvPrice), which is the *average* of the prices observed in the market for a given product from period 1 to period t-1, where t is the period of play, or alternatively lagged minimum price (LagMinPrice), which is the minimum price experienced

[9] Unsurprisingly, the one effect of rationing we find in Experiment 1 is that subjects that are rationed in one period are more likely to demand more the following period.

[10] Sashegyi et al. (2000) argue that, for this kind of data, where observations over time are taken for different group of subjects, an econometric model must control both for intra-cluster correlation and intra-individual correlation within the same cluster. For our data, panel models are the most appropriate, and specifically more appropriate than spatial models (such as error clustering). See Baltagi et al. (2006) for further discussion.

[11] Since proxies for past prices are used in the regressions, only observations from period 2 are included.

so far, i.e. the *minimum* of the prices observed in the market for a given product from period 1 to period t-1.

(*Insert Table 6 about here*.)

If past prices matter, then the dynamic pricing strategy employed by firms may matter. Such dynamic strategy, however, differs between Experiment 1 and 2. In Experiment 2, prices are consistently fixed either in a low range or in a high range, whereas prices in Experiment 1 are much more spread all over the place. The average observed variance in the computer generated prices chosen by each firm in Experiment 2 is 34.66 in the low price distribution and 33.04 in the high price distribution.[12] The median is respectively 34.64 and 34.65. Conversely, in the market treatments, the average variance of prices chosen by each firm is 384.22 and the median is 90.14. The variance is significantly higher in the market treatments than that in the individual choice treatments (F test, p = 0.00).

As a result, if we assume that preference shaping will occur more in relation to complex products since buyers find more difficult to ascertain the true value of these products, consumers may be exploitable in Experiment 2 in a way they are not in relation to Experiment 1, since they are faced with a more systematic pricing strategy in Experiment 2. This leads to include not only an IC dummy variable taking the value of 0 in Experiment 1 and 1 in the individual choice Experiment 2, but also to include interaction terms of this variable with the past price variable in each regression model, i.e. LagAvgPrice × IC and LagMinPrice × IC.

Additional variables we have in the regression models include the current price (Price), a Complex dummy equal to 1 for complex products and 0 for simple ones and the period number between 2 and 40 (Period). We also include Price × IC and Complex × IC interaction terms.

The regressions in Table 6 confirm the existence of a significant negative relationship between price and quantity, as already discussed. IC has a significant positive coefficient,

[12] These values are computed by looking at each set of prices chosen for each product by each firm during a session.

implying that more is bought in the individual choice treatments, while Price × IC also has a significant coefficient, implying greater sensitivity to the price observed in the individual choice treatments of Experiment 2. The coefficient on Period is negative and strongly significant: the quantity bought and demanded decreases with time.

While the coefficient on Complex is generally not statistically significant,[13] the one on Complex × IC shows a robust and statistically significant positive coefficient: on average, controlling for the other regression variables including the product price, buyers bought more of the complex product than of the simple one. This result chimes with the earlier result of a net complexity exploitation effect at least in the context of the IC2 treatment.

The coefficients on LagAvgPrice and LagMinPrice are positive and statistically significant, showing evidence of a shaping effect across both Experiments 1 and 2. However, these coefficients are smaller than those on the interaction terms LagAvgPrice × IC and LagMinPrice × IC. Shaping occurs more strongly in the individual choice treatments than in the market treatments.

RESULT 4. Preference shaping occurs. Controlling for other factors such as current prices, past experience with prices influences consumers' willingness to purchase products.

RESULT 5. There is no statistically significant evidence of an aggregate net complexity aversion effect, while there is some evidence of an aggregate net complexity exploitation effect in quantities bought and demanded with the computer generated pricing strategies of Experiment 2, especially in relation to the IC2 treatment.

To verify further the extent to which consumer exploitability is a possibility, it might be helpful to consider quantities bought when there are high prices. For comparability between Experiment 1 and Experiment 2, we consider prices between 75 and 95, as high prices in Experiment 2 are randomly generated within this range only.

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[13] Regression model 3 is the only one where there is evidence of marginal statistical significance (only at the $P < 0.1$ level).

(*Insert Figure 4 about here*.)

Figure 4 shows that quantities bought are virtually the same in the B and IS1 treatments, while they nudge in the direction of consumer exploitation in the remaining Experiment 1 treatment (IS2) and in both Experiment 2 treatments.[14] When the high pricing strategy is used systematically, as in the individual choice treatments IC1 and IC2, the quantity bought of complex lottery is significantly higher than that for simple one (Wilcoxon p = 0.04). The difference is also significant if we consider the treatments where the products were on sale simultaneously (IS2 and IC2, Wilcoxon p = 0.08). If we consider IC1, IC2 and IS2 altogether, the statistical significance increases (Wilcoxon p = 0.02). These results are confirmed if we look at the difference in the expenditure between complex and simple product.[15]

Result 6. There is evidence for some potential consumer exploitability: when prices are high, it is possible for firms to exploit consumers into buying more of the complex products than they would otherwise (i.e., were they more certain about their value as in the case of simple products).

4. Discussion and Conclusion

The key motivation of our experiments was to provide a first preliminary study on whether product complexity affects competition. This required us to identify a metric of product complexity that controls for consumer preferences, and we relied on Sonsino et al. (2002) to construct a procedure enabling us to do so. Our metric translates product complexity into an inability by subjects to understand what the value of the product is, which can be justified in terms of combinations of possible utility outcomes that can be obtained by multiple product features. Our procedure for identifying product complexity was validated by

[14] Due to the negative relationship between prices and quantities (Result 3 above), of course mean quantities in Figure 4 are generally lower than those in Figure 4, as they refer to high prices only.
[15] The expenditure is significantly higher for the complex lottery than for the simple one both in the individual choice treatments (IC1 and IC2) and in treatments where both products are on sale simultaneously (IS2 and IC2) (Wilcoxon p = 0.03 and 0.08, respectively). If we consider all three treatments the statistical significance lies between the two (Wilcoxon p =0.04).

the longer time buyers spent in making decisions for complex products than for simple ones, though undoubtedly future research may wish to consider other ways of varying product complexity building on this work, as our results might be sensitive to the procedure used.

While Sonsino et al. (2002) claim evidence for complexity aversion, and mainly theoretical research (which is in the spirit of the OFT policy report by Garrod et al., 2008) suggests that complexity exploitation is an issue, we could not detect any significant evidence of either complexity aversion or exploitation in relation to prices; if there is complexity aversion, it has only a small and temporary effect on prices. We did find that, in Experiment 2 where pricing strategies were computer generated and exhibited lower variance than in Experiment 1, there is some evidence of a complexity exploitation effect in quantities: that is, for a given price, more is bought of the complex product than of the simple one. The possibility of consumer exploitability is confirmed by considering consumer behavior when prices were high. Demand for complex products was more elastic than demand for simple products. Consumers may also be exploited not just because of their uncertainty about the value of the products, but more fundamentally because their preferences are uncertain in the first place: as a result, they may anchor their valuation on past experience. This suggests that firms who engage in consistent (lower variance) pricing behavior may be more effective in selling to consumers.

It could be argued that the interpretation of differences in quantities bought for a given price is not really a form of exploitation. We accept the plausibility of this alternative interpretation, although, to counter it, we note that uncertainty about the value of the product is a form of bounded rationality and as such in our view it is normatively appropriate to consider this as a form of exploitation relative to what the consumer would be doing were he or she not confused by the product. In this sense, while further research is clearly needed, there is some *qualified* support for the claim that consumers may be harmed by product complexity, even though prices are not systematically altered.

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Figure 1. Mean Price Dynamics

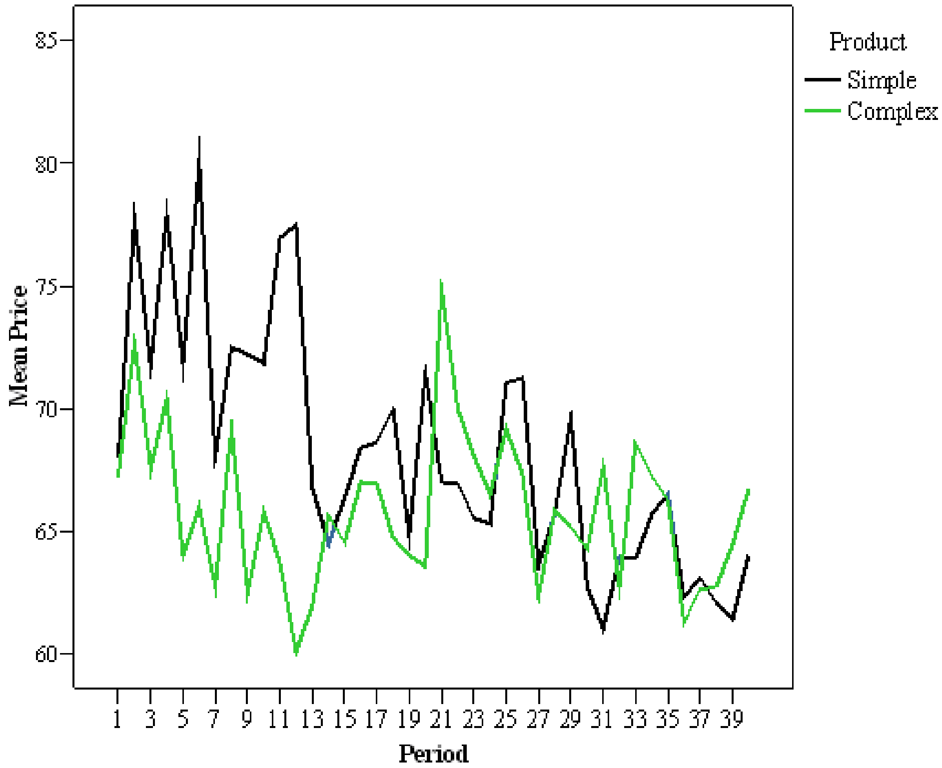
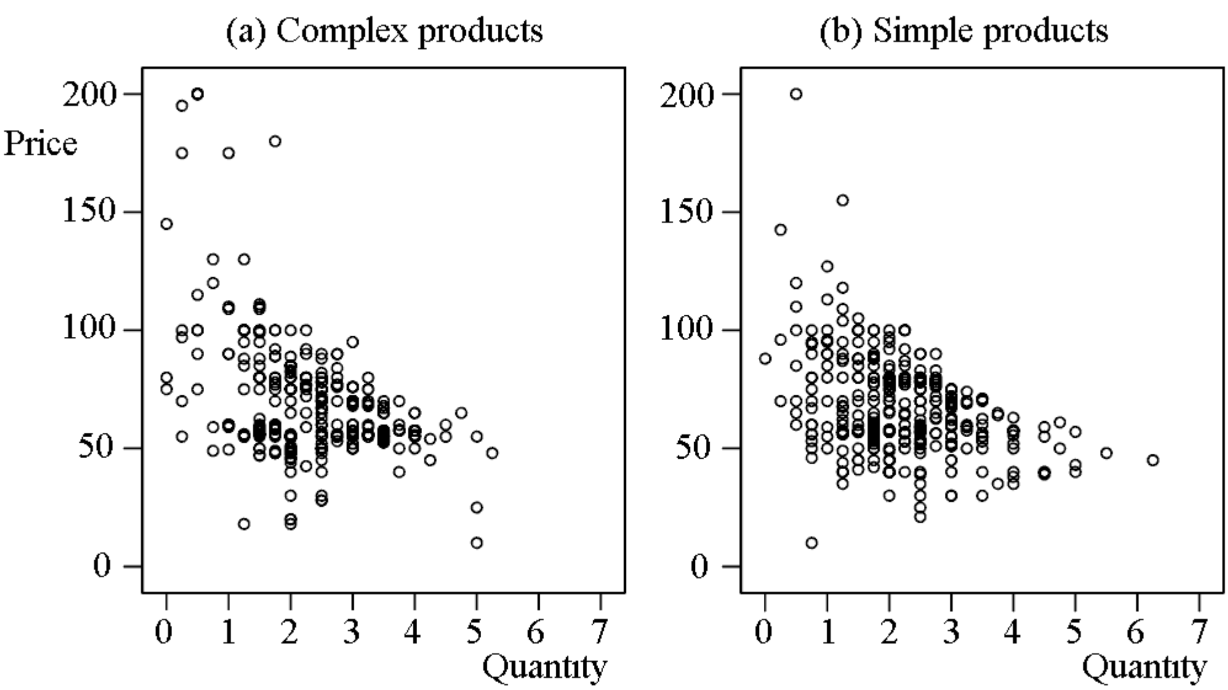
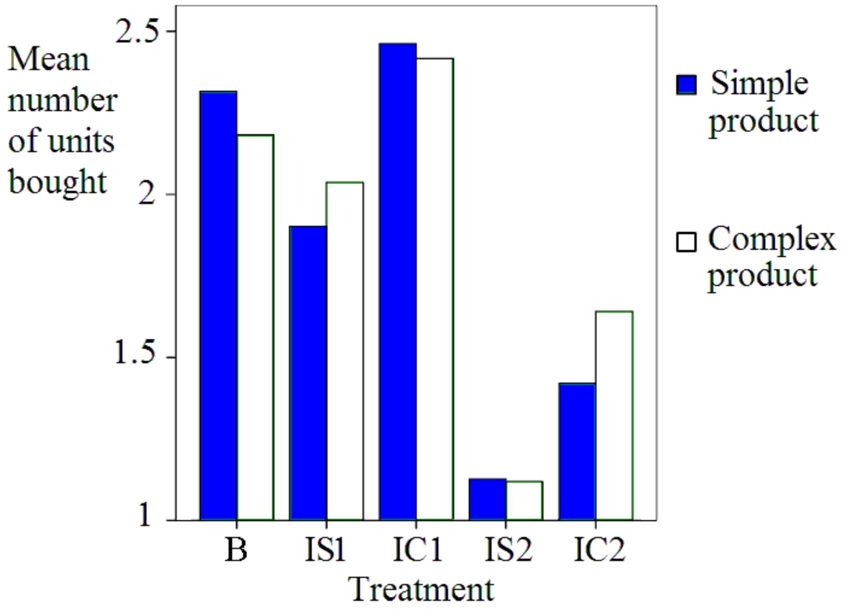


Figure 2. Demand Schedules Scatterplots for Simple and Complex Products



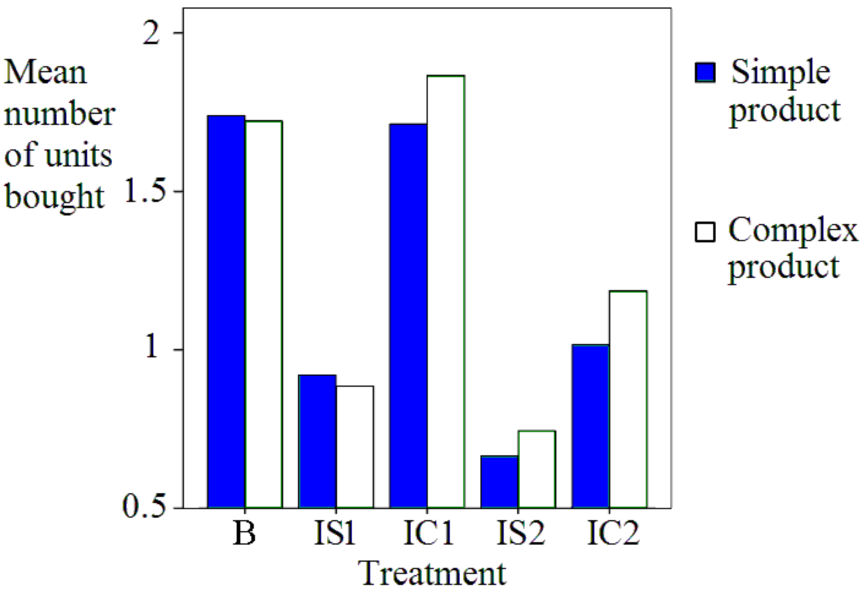
Note: Each dot corresponds to an observed (price, quantity) combination in either of the two experiments.

Figure 3. Average Number of Units Bought By Treatment



Note. Experimental treatments are as defined in the main text.

Figure 4. Average Number of Units Bought when Prices are Between 75 and 95



Note. Experimental treatments are as defined in the main text.

Table 1. Simple Products

Simple Product 1 (S1)			Simple Product 2 (S2)		
Outcomes	Probability	Results	Outcomes	Probability	Results
1	0.5	10	1	0.5	3
2	0.2	65	2	0.2	66
3	0.3	140	3	0.3	151

Note. Results are in experimental points.

Table 2. Complex Products

Complex Product 1			Complex Product 2		
Outcomes	Probability	Results	Outcomes	Probability	Results
1	7.50%	13.9	1	7.50%	7.44
2	3.00%	63.4	2	3.00%	64.14
3	12.50%	10	3	12.50%	3
4	2.70%	140	4	2.70%	151
5	7.50%	19.1	5	7.50%	13.36
6	2.00%	61.15	6	2.00%	61.59
7	1.80%	137.75	7	1.80%	148.45
8	3.00%	130.85	8	3.00%	140.61
9	2.00%	15.5	9	2.00%	9.3
10	4.50%	136.1	10	4.50%	146.56
11	1.80%	72.5	11	1.80%	74.5
12	3.00%	128.65	12	3.00%	138.09
13	5.00%	11.65	13	5.00%	4.89
14	5.00%	59.5	14	5.00%	59.7
15	7.50%	127	15	7.50%	136.2
16	4.50%	130.9	16	4.50%	140.64
17	1.80%	134.75	17	1.80%	145.05
18	1.20%	70.25	18	1.20%	71.95
19	1.20%	67.25	19	1.20%	68.55
20	1.20%	132.5	20	1.20%	142.5
21	0.80%	65	21	0.80%	66
22	4.50%	23	22	4.50%	17.8
23	2.00%	63.35	23	2.00%	64.11
24	3.00%	17.75	24	3.00%	11.85
25	3.00%	68.6	25	3.00%	70.06
26	5.00%	13.85	26	5.00%	7.41
27	3.00%	20.75	27	3.00%	15.25

Note. Results are in experimental points.

Table 3. Marginal Cost Function for each Unit of the Product Sold by Sellers

Unit	Cost
1st & 2nd	5
3rd & 4th	5
5th & 6th	10
7th & 8th	10
9th & 10th	47.5
11th & 12th	50
13th & 14th	52.5
15th & 16th	55
17th & 18th	57.5
19th & 20th	60
21st & 22nd	62.5
23rd & 24th	65
25th & 26th	67.5
27th & 28th	70
29th & 30th	72.5
31st & 32nd	75
33rd & 34th	77.5
35th & 36th	80
37th & 38th	82.5
39th & 40th	85

Note. Costs are in experimental points.

Table 4. Experimental Design and Number of Independent Observations

	Treatment	Subjects	Independent observations
Experiment 1	B	80	16
	IS1	60	12
	IS2	60	12
Experiment 2	IC1	32	16 (high prices) + 16 (low prices)
	IC2	36	18 (high prices) + 18 (low prices)

Note. Experimental treatments are as defined in the main text.

Table 5. Average Values of Key Variables

		Experiment 1			Experiment 2	
Variable	Product	B	IS1	IS2	IC1	IC2
Price	Simple	70.00	70.27	66.15	70.31	70.00
	Complex	66.97	66.15	65.48	70.40	69.94
Quantity Bought	Simple	2.32	1.88	1.13	2.46	1.42
	Complex	2.18	2.09	1.12	2.42	1.64
Quantity Demanded	Simple	2.72	2.32	1.41	2.46	1.42
	Complex	2.70	2.44	1.30	2.42	1.64
Expenditure	Simple	148.78	113.21	71.61	156.49	89.77
	Complex	137.58	120.97	69.41	156.93	103.65
Response Time Buyers	Simple	12.88	10.34	-	11.61	-
	Complex	15.63	12.72	-	14.06	-
Response Time Sellers	Simple	20.75	19.02	-	-	-
	Complex	23.31	19.09	-	-	-

Table 6. Regression Analysis

Dependent Variable:	Quantity Bought			Quantity Demanded		
	Model 1			Model 2		
Regressors	Coef.	Std. Err.	P>z	Coef.	Std. Err.	P>z
Price	-0.020	0.001	0.000	-0.036	0.001	0.000
IC	2.985	0.519	0.000	1.483	0.568	0.009
PricexIC	-0.104	0.004	0.000	-0.088	0.005	0.000
LagAvPrice	0.003	0.002	0.082	0.007	0.002	0.000
LagAvPricexIC	0.064	0.007	0.000	0.064	0.008	0.000
Complex	-0.041	0.034	0.222	-0.037	0.042	0.380
ComplexxIC	0.185	0.058	0.002	0.197	0.076	0.009
Period	-0.006	0.001	0.000	-0.010	0.002	0.000
Constant	3.124	0.114	0.000	4.239	0.215	0.000
Dependent Variable:	Quantity Bought			Quantity Demanded		
	Model 3			Model 4		
Regressors	Coef.	Std. Err.	P>z	Coef.	Std. Err.	P>z
Price	-0.020	0.001	0.000	-0.035	0.001	0.000
IC	4.441	0.337	0.000	2.882	0.491	0.000
PricexIC	-0.101	0.004	0.000	-0.083	0.005	0.000
LagMinPrice	0.005	0.001	0.000	0.007	0.002	0.000
LagMinPricexIC	0.042	0.005	0.000	0.042	0.007	0.000
Complex	-0.058	0.034	0.089	-0.060	0.042	0.156
ComplexxIC	0.204	0.059	0.001	0.218	0.076	0.004
Period	-0.005	0.001	0.000	-0.009	0.002	0.000
Constant	3.051	0.106	0.000	4.374	0.193	0.000

Notes: n = 12168; data from period 2 onwards included; random effect regressions used controlling for the non independence of each time series of observations in relation to each session (Experiment 1) or subject (Experiment 2).