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## **Obfuscation in Competitive Markets**

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### **ABSTRACT**

In many markets, firms make their products complex through add-ons, thus making them difficult to evaluate and compare. How does this product obfuscation affect competition, sellers' profits, and buyers' welfare? We study these questions in a competitive experimental market in which sellers have the opportunity to obfuscate by add-on features, and buyers endogenously decide how much time to spend on searching for the best product. We show that stable obfuscation levels emerge that reduce buyers' welfare by ensuring that total prices are substantially above marginal cost and by inducing buyers to make mistakes and to waste their time searching. Competition operates through lowering salient headline prices, but sellers are able to appropriate a considerable share of the surplus with expensive add-on features. In contrast, prices quickly converge to marginal cost if we remove obfuscation opportunities. We thus provide direct causal evidence that obfuscation mitigates competition and generates positive profits because buyers typically search only a small share of the product space. Our results also suggest that purely exploitative obfuscation tends to be much less stable than obfuscation by surplus-enhancing add-on features because buyers' aversion to complicated products may have a non-negligible impact on sellers' obfuscation decisions.

### 1 Introduction

Complex products and price schedules are a prevalent feature of modern economies. Complexity, however, comes with its own problems because it makes products difficult to evaluate and compare across competing sellers, and firms often appear to deliberately obfuscate the true values and prices of their products. For example, printers and cameras are often combined with complex bundles of differently priced add-ons and accessories. Electronic products like personal computers and memory modules advertise low prices for a very basic product with limited memory, low capacities, and short warranties, but offer many kinds of complex upgrades separately. Similar situations have been proliferating in many industries and marketplaces (Greenleaf et al., 2016; Ellison and Ellison, 2018).

Thus, obfuscation opportunities exist in many markets, and a key question is how do these markets work? Do sellers always use the obfuscation opportunities, and why? If sellers use them, how do they affect market prices, sellers' profits, and consumer welfare? In particular, do obfuscation opportunities enable sellers to enforce prices above marginal cost and thus ensure stable profits in the long run in markets that would otherwise be very competitive? And if so, what are the competition-mitigating mechanisms that enable positive profits and reduce buyers' welfare? Is it because buyers make more mistakes, as obfuscation prevents them from finding the best product in the market? Or does obfuscation mitigate the buyers' responses to over-priced add-on features? Or do consumers waste too much valuable time in searching?

There is a considerable theoretical literature indicating that obfuscation may mitigate market competition and sellers may therefore be able to earn higher profits (e.g., Ellison, 2005; Spiegler, 2006; Gabaix and Laibson, 2006; Carlin, 2009; Wilson, 2010; Spiegler 2011; Ellison and Wolitzky, 2012; Piccione and Spiegler, 2012; Chioveanu and Zhou, 2013; Heidhues, Kőszegi and Murooka, 2017; Hefti, Liu and Schmutzler, 2020). The empirical literature has found mixed evidence for these predictions. For example, Chetty, Looney and Kroft (2009) show that the demand elasticities are lower when taxes are shrouded compared to when they are not shrouded; Muir, Seim and Vitorino (2013), Seim, Vitorino and Muir (2017a) and Célérier and Vallée, 2017 show that higher prices or markups are associated with more complex products and shrouded add-ons. However, Hossain and Morgan (2006) and Brown, Hossain and Morgan (2010) find that shrouding surcharges does not improve or even decreases revenues compared to unshrouding them, and Chiles (2017) shows that shrouding surcharges in fact decreases sellers' reputation.<sup>2</sup> Therefore, current evidence seems somewhat inconclusive about how competitive

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<sup>&</sup>lt;sup>1</sup> Other examples involve price quotes of airlines that typically do not include fuel surcharges and the extra fees required for the right to change or cancel booking, checking luggage, seat reservation, travel insurance, and so on. Hotel rooms may have many extra services, cleaning surcharges, and resort fees that are hard to find out. Similarly, many financial products advertise their attractive aspects (e.g. high return rates) but shroud their downsides with complex descriptions. Insurance and healthcare companies as well as banks frequently offer contracts with many different combinations of contingencies and reimbursement practices, often associated with jargon that is hard for most consumers to comprehend.

<sup>&</sup>lt;sup>2</sup> Similarly, Ellison and Ellison (2009) show that lower headline prices for base products are associated with more demand for pricy upgraded products, but Hossain and Morgan (2006) find that lower opening prices in auction markets do not attract more bidders or bring higher revenues. In addition, Richards et al. (2020) interpret their retail sales data from consumer-packaged goods as evidence of strategic obfuscation, but Miravete (2013) suggests that competition in the early US cellular telephone industry does not foster the use of obfuscation.

markets with obfuscation opportunities work and important questions mentioned above still remain unsolved.

This is not surprising because many of the questions are hard to answer empirically, as they require knowledge about production technologies, costs, sales, profits, as well as consumers' valuation of products, search costs, and buying mistakes. Researchers often do not have access to this type of information in field data, especially on the market level. Welfare judgments are, in particular, hard to derive in the absence of information about consumers' preferences for products and product attributes. Likewise, reliable knowledge about what would happen, *ceteris paribus*, in the absence of obfuscation or with different forms of obfuscation is hard to obtain; but these counterfactuals are crucial for the identification of the conditions under which obfuscation is profitable and sustainable. In addition, understanding how and why obfuscation works requires knowledge about how exactly obfuscation mitigates competition. However, direct evidence on these mechanisms is difficult to obtain because data on how buyers make their buying decisions in the presence and in the absence of obfuscated products are typically not available.

In order to answer these questions, we designed a laboratory experiment that captures a competitive market with obfuscation opportunities through add-ons and compares this market with a competitive control market that removes obfuscation but is otherwise identical. In particular, buyers in the control market without obfuscation have access to transparent information about the overall net value of all products, while time and mental search costs generated by complex add-ons may prevent buyers from obtaining full transparency in the market with obfuscation opportunities.

We find that sellers in markets with obfuscation opportunities are able to appropriate a substantial part of the total surplus that buyers would have received if the prices were at marginal costs. Even in the long run, sellers can appropriate roughly one third of this surplus. 63% of the buyers' welfare loss is caused by high prices because even the best available products in these markets are priced significantly above marginal cost. The remaining 37% of the welfare loss is due to buyers' errors in identifying the best product in the market because trading prices remain dispersed even in the long run. These findings contrast sharply with the control treatment where the market quickly converges to marginal-cost pricing after only a few periods. Moreover, as buyers make almost no buying errors in the control treatment, the best product almost always serves the entire market independent of other products available in the market, indicating strong competitive forces. Sellers with obfuscation opportunities are therefore able to escape the "zero-profit" trap even in otherwise very competitive markets. In addition, roughly 12% of the total surplus is lost in the market with obfuscation opportunities because buyers wasted time in searching the market and trade was insufficient likely due to buyers' mistakes.

Why are sellers able to mitigate competition to such an extent that they can earn relatively high profits in the market with obfuscation opportunities? The key reason is that they make ample use of obfuscation and make their products overly complex, which has a strong impact on buyers' behavior. Despite the fact that buyers waste time in searching the market that is roughly worth 10% of the total surplus, they include less than half of the available products in their consideration sets; and they only see around half of the products' add-on features even for those products that they visit. We find that sellers exploit this pattern of buyers' search behaviors by strategically placing the best add-ons (i.e. those with the highest net value for the buyer) at the top of the add-on list, while the worse add-ons are placed at the end. However, buyers are often not aware of the bad add-ons because they rarely look at all add-ons of a

product. As a consequence, usually more than half of the buyers are not aware of which product is the best available product in the market. Thus, while the best available product is transparent and attracts almost all buyers in the market without obfuscation, the best available product in the market with obfuscation opportunities has only a very limited impact on other sellers' ability to sell their "worse" product. Therefore, even very "bad" products have a high chance of being sold in this market, and this affects both the average market outcome and buyer welfare.

Despite the fact that obfuscation renders products quite opaque for the buyers, competition is not completely eliminated in this market. We find that buyers pay a lot of attention to the transparent aspect of a product, i.e., they are attracted by low headline prices: a reduction in the lowest headline price in the market significantly impairs the sales of other sellers, indicating that competition operates via headline prices. Sellers respond to this competitive pressure with substantial and quick reductions in headline prices. In fact, headline prices even fall below the marginal cost of the base products (i.e., the product without add-ons) over time. However, buyers appear to be much less sensitive to the prices of add-ons, enabling sellers to appropriate a considerable and stable share of the surplus available in the market via add-on features.

The results mentioned above are in treatments where the add-on features generate extra surplus to the product. We believe that this aspect of our design captures the characteristics of many naturally occurring markets.<sup>3</sup> However, obfuscation may not always take the form of surplus-enhancing add-on features. Therefore, we also implemented a treatment where add-on features do not generate any extra surplus because the cost of an add-on always equals the value it generates for the buyer. In this treatment, the only effect of add-on features is that the total price of the product, which could have just been shown in one all-inclusive headline price, is partitioned into the more complicated add-on features that require buyers to spend extra time to understand the product. This treatment therefore captures purely exploitative obfuscation opportunities that only serve the purpose of increasing consumers' search cost – a situation that is at the center of most theories of obfuscation (Spiegler, 2006; Carlin, 2009; Ellison and Wolitzky, 2012; Chioveanu and Zhou, 2013). Our design enables us to examine whether stable and high obfuscation levels also robustly emerge in this environment.

We observe that obfuscation levels in this environment are lower and more fragile than in the other treatments where add-ons are surplus-enhancing. Our data reveal a clear bi-modal pattern when add-ons are not surplus-enhancing: in half of the markets, obfuscation maintains itself at high levels; but in the other half of the markets, obfuscation decreases over time to rather low levels. An analysis of buyers' buying behavior suggests that a potential reason for the fragility of obfuscation in the latter group of markets is that buyers refrain from buying products with many add-ons, even after controlling for the products' overall values and prices. This aversion to complex products in the market with surplus-neutral add-ons appears to generate a counter-force to individual seller's incentive to obfuscate, which can explain why obfuscation is fragile in these markets. But why do buyers display complexity aversion in the markets with surplus-neutral add-ons but not in the market with surplus-enhancing add-ons? A possible reason appears to be that the relationship between the aggregate net value of the add-ons for the buyers in the latter is *positively* related to the complexity of the product, while this relationship is

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<sup>&</sup>lt;sup>3</sup> For example, add-ons like accessories to printers and cameras generate value for consumers. Likewise, additional working memory for electronic products or the right to cancel a flight or to reserve a seat is also valuable for consumers.

*negative* in the market with surplus-neutral add-ons. In other words, when add-ons are surplus-enhancing, a product with a higher number of add-ons is typically a better product for the buyers, while more add-ons indicate a worse product for buyers when they are surplus-neutral. We document that buyers, on average, notice that higher complexity means that products are worse in the markets with surplus-neutral add-ons, which potentially explains that they shy away from buying complex products, thus rendering obfuscation more fragile.

Our study contributes to the literature on obfuscation, boundedly rational consumers, and behavioral industrial organization in a number of ways. First, we provide new and direct tests for a number of predictions of theoretical models of obfuscation (Ellison, 2005; Spiegler, 2006; Gabaix and Laibson, 2006; Carlin, 2009; Ellison and Wolitzky, 2012; Piccione and Spiegler, 2012; Chioveanu and Zhou, 2013; Heidhues, Kőszegi and Murooka, 2017). Specifically, we show clear evidence supporting the prediction that obfuscation opportunities enable sellers to earn positive and sizable profits even in otherwise very competitive markets. We are able to compute the size of buyers' welfare loss and the efficiency losses compared to a control market in which fully competitive outcomes are quickly obtained. We empirically identify the main competition-mitigating mechanism: buyers examine the product and add-on space insufficiently, meaning that they often fail to identify the best product in the market. They are therefore overly attracted by the transparent part – the headline prices – of products, even though they are aware of the potential existence of pricy add-ons. But buyers exhibit low sensitivity to the prices of add-on features because of search costs, allowing sellers to earn stable positive profits.

In this context, it is also worthwhile to point out that sellers' behavior makes perfect sense in view of how buyers respond to prices and obfuscation. Because buyers respond very sensitively to headline prices, sellers face an incentive to reduce them, and, as a consequence, they vigorously compete by lowering headline prices. In fact, this competition is so strong that headline prices even converge below the base product's marginal cost. In contrast, because buyers show little behavioral sensitivity to add-on prices, competition via add-on prices is so weak that sellers can enforce stable and sizeable profits through pricy add-ons. Likewise, in anticipation of buyers' limited search in the add-on space, the sellers deliberately place the best add-ons more visibly while hiding the worst ones. Thus, major aspects of seller behavior are consistent with profit-maximizing behavior.

Second, our findings may inform future theorizing about markets with obfuscation opportunities and lead to the modelling of aspects that have not been widely discussed in the theoretical literature. This concerns, in particular, the role of complexity aversion as a potential counterforce to obfuscation. Recall that our results suggest that whether add-ons are surplus-enhancing has potentially important implications for the stability of obfuscation in the market. While obfuscation and the patterns described in the previous paragraphs are very stable in environments with surplus-enhancing add-ons, obfuscation becomes more fragile in environments where add-ons do not increase the surplus but only raise buyers' search cost. In the latter environment, we find indications that buyers' aversion to complex products constrains sellers' obfuscation behavior. While complexity aversion is consistent with the empirical finding that consumers value transparency (Seim, Vitorino and Muir, 2017a) or give lower ratings to products with hidden surcharges (Chiles, 2017), this literature does not examine whether and under which conditions complexity aversion becomes behaviorally relevant for sellers' obfuscation decisions and for market outcomes. Our results suggest that while complexity aversion may become important

under purely exploitative obfuscation, it appears to be offset by obfuscation with attractive surplusenhancing add-on features and thus becomes unable to destabilize obfuscation at the market level.

Finally, our paper also contributes to the experimental literature related to obfuscation and bounded rationality in consumer behavior. One part of this literature studies boundedly rational individual decision-making in complex situations such as in a complex product space (Crosetto & Gaudeul 2011; Jin, Luca and Martin 2015; Kalayci & Serra-Garcia 2016; Sugden and Zheng 2018). Many lab experiments in marketing also typically study this type of situation (see Greenleaf et al. 2016 for a review). These experiments neither allow for interactions in markets nor is there competition among the players. The other part of the literature (Kalayci and Potters, 2011; Kalayci, 2015, Gu and Wenzel 2015; Kalayci 2016; Crosetto and Gaudeul 2017) studies obfuscation in market environments. However, none of the papers mentioned above shows that surplus-enhancing obfuscation opportunities enable the sellers to escape the zero-profit trap by enforcing stable long-run profits in an otherwise competitive environment. In addition, the previous experimental literature does not implement the important distinction between relatively salient headline prices and the prices and values of add-ons that buyers typically can only learn gradually through investments in search effort. Recall that this feature enables us to identify the major source of sellers' capability to enforce positive long-run profits: while sellers fiercely compete with their headline prices, the obfuscated characteristics of add-ons enable them to strongly reduce competition in add-on prices in response to buyers' limited search in add-ons. Moreover, the previous experimental literature did not implement the potentially important distinction between surplus-enhancing and surplus-neutral add-ons, which enabled us to discover conditions under which obfuscation appears to be more fragile.

The rest of the paper is organized as follows. In Section 2, we describe the design of the market with obfuscation opportunities, the control market with no obfuscation, and other treatment variations that we implemented. After that, we discuss important design features of the experiment in the context of the current literature and potential outcomes of the experiment. Section 3 reports the empirical results. It first presents the overall market outcomes and then examines sellers' obfuscation strategies and buyers' behavior in treatments with surplus-enhancing add-on features. We show how the results from the treatment with surplus-neutral add-on features differ in the final part of Section 3. Section 4 concludes.

### 2 Experimental Design

In this section, we first discuss some key issues in developing an experimental design that enables the examination of the causal consequences of obfuscation on the behavior of market participants and market outcomes in a highly competitive environment.

When studying the causal consequences of obfuscation in a competitive environment, one needs to compare a competitive market with obfuscation opportunities ("OO market") with a control treatment that is identical in every respect except that the sellers can no longer obfuscate their products (market with no obfuscation, denoted as "NO market"), i.e., the buyers can fully understand the nature of the offered products without any cost. In principle, any complexity in the overall product design – the physical product properties, the number, the characteristics, and the values of add-ons for the consumers as well as the structure of add-on prices – can make it difficult for consumers to assess the true overall

net value of a product. For example, consumers may find it difficult to assess the subjective values of the various add-ons because they are uncertain about their value, or some add-ons may be substitutes whiles others may be complements. All these forms of complexity associated with add-ons may require consumers to spend substantial extra time assessing the overall value and the overall price of the good. Whatever the features that prevail in the OO market, the control treatment also needs to allow for the same features but nevertheless remove obfuscation opportunities.

In our experimental design – described in more detail below – we choose a form of obfuscation opportunity that enables us to achieve this goal. Sellers are given the opportunity to add extra features to their basic product, but each extra feature has a well-defined objective value for the buyers, and the price of each extra feature is also available for the buyers to observe; but because there are potentially many extra features the buyers may have to incur some time cost to view them, compute the overall value of a product, and compare the products in the market. In contrast, obfuscation is removed in the control treatment by informing the buyers transparently about the *overall* objective value of *each* product in the market, which renders the market very transparent.

Ideally, our design should generate competitive outcomes in the control market without obfuscation, i.e. consumers should appropriate the whole surplus in the market. By comparing the market with obfuscation opportunities with the control market, we can then study the extent to which obfuscation opportunities enable firms to escape the "zero-profit trap", i.e., whether they can appropriate part of the available surplus through obfuscation in an otherwise very competitive environment.

### 2.1 A market with obfuscation opportunities

In a market, 16 participants interact in a posted-offer institution for 20 trading periods. Among the 16 participants, 6 of them are randomly assigned to be sellers and the other 10 of them are assigned to be buyers throughout the entire 20 trading periods. The sellers and buyers trade experimental goods that are labelled as phones. Each phone consists of a basic phone and some extra features. Sellers can offer basic phones by incurring a marginal production cost of 5 Experimental Currency Units (ECU), while buyers' valuations of a basic phone differ. In each period, a buyer's valuation of a basic phone is a random value out of five possible values: 0, 5, 10, 15, or 20 ECU; each of the five possible values is randomly assigned to two of the buyers in any given trading period. <sup>4</sup> In each trading period, sellers can set a base price for their basic phone. Each buyer can buy a maximum of 1 unit, but each individual seller can serve the demands of all buyers. As 6 sellers are competing with each other for 10 buyers with no limits in supply, we ensure that the market is very competitive.

On top of the basic phone, sellers can also add extra features to their products. Figure 1 shows an example of how these products are presented in the experiment. Each extra feature has a label, a value, and a price. Each feature provides buyers of this product with the corresponding additional value on top of their own basic values, but generates an additional production cost for the seller. In our first treatment, the production cost for producing any additional value is always 50% of that value. Add-on features

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<sup>&</sup>lt;sup>4</sup> More specifically, each buyer is randomly assigned to one sequence of basic values across the 20 trading periods that makes sure each buyer experiences each basic value for 4 periods. These sequences of basic values also ensure that each of the five possible basic values is assigned to two buyers in each period. Note also that a buyer who is randomly assigned a basic value of zero may nevertheless be able to conclude a mutually beneficial trade because the sellers can add value-enhancing features to a basic phone.

thus always increase the total available surplus in this treatment. We also implemented treatments in which additional features are not always surplusenhancing. We describe these treatments and their rationales in more detail in section 2.3. The add-on prices, on the other hand, represent additional charges for the respective add-on feature.

This design maps the real-life situations in which firms separately list or add many features to their products, like technical properties, quality upgrades, extended warranties, additional accessories, shipping, extra services, etc. While these features are often indeed valuable for consumers and presumably surplus-enhancing, they also increase the product's complexity, as products are all differentiated along these dimensions and their prices also vary.

For simplicity, buyers of any product need to buy all the extra features that come with the product. This design captures many cases in naturallyoccurring markets. First, the listed features and add-ons for many products

# Figure 1 Base Price: 20 Features: Label Value Price shipping: 7 4 display: 9 5 capacity: 3 6 camera: 3 3 warranty: 2 4

are indeed inseparable components of the product. For example, many "features" in bundle sales and composite products like camera packages or insurance products are indeed parts of the full products. Likewise, printers or phones may be designed in such a way that consumers can later only use the ink or the earphones that are compatible with the original products. Second, buyers often already have a product with certain features in mind that they would like to buy before a purchase. For example, when consumers book flight tickets, they know whether they need to have the right to change their bookings in the future or how many bags they need to check. Therefore, even though these features appear optional, they are in fact necessary for those consumers who have a relatively fixed demand for those features. Third, even when add-ons are actually optional, firms often design the descriptions of the products so that the basic product looks significantly worse than the upgraded product with add-ons (Ellison and Ellison, 2019), which entices consumers to actually buy the add-ons. Therefore, our experimental design can be interpreted as capturing a situation in which a consumer who buys a seller's product also buys the add-ons of this product. Finally, note that different firms may indeed offer different add-ons in the experiment. Thus, by deciding from which firm to buy, the buyer has still some discretion about the add-on he or she is buying.

In this setting, we can denote buyers' basic value as  $v_b$ , the base price as  $p_b$ , and sellers' marginal cost of producing a basic phone as  $c_b$ . For a product with n extra features, suppose the value and price of the  $i^{th}$  feature is  $v_f^i$  and  $p_f^i$  respectively, then we can denote  $v_f = \sum_{i=1}^n v_f^i$  as the aggregate feature value for a product with n extra features,  $c_f(v_f)$  as the aggregate cost of producing  $v_f$  and  $p_f = \sum_{i=1}^n p_f^i$  as the aggregate feature price. Then, from the sellers' perspective, their profits per unit sold,  $\pi^S$ , is given by their earnings from both the basic phone  $\pi_b^S$  and the extra features  $\pi_f^S$ , which can be calculated as<sup>5</sup>:

$$\pi^{S} = \pi_{b}^{S} + \pi_{f}^{S} = (p_{b} - c_{b}) + (p_{f} - c_{f}(v_{f}))$$

<sup>&</sup>lt;sup>5</sup> Each seller also receives a fixed payment of 3 ECU independent of profit from sales in a period, so that even if some sellers do not sell anything in several periods, they are still compensated to maintain the motivation to participate in the experiment.

From the buyers' perspective, their total earnings from buying a product,  $\pi^B$ , is given by the earnings from both the basic phone  $\pi^B_b$  and the extra features  $\pi^B_f$ , which can be calculated as:

$$\pi^{B} = \pi^{B}_{b} + \pi^{B}_{f} = (v_{b} - p_{b}) + (v_{f} - p_{f})$$

### The Seller Stage

The market described above contains 20 trading periods, and each trading period consists of 3 stages: "Seller Stage", "Buyer Stage", and "Feedback Stage". In the "Seller Stage", sellers decide which product they want to offer. To simplify the sellers' decisions, we do not require them to fix a separate value and a separate price for each extra feature they provide. Rather, in addition to setting a non-negative base price, they only need to determine the number of features n, the aggregate feature value,  $v_f$ , and the aggregate feature price,  $p_f$ . Given the chosen levels of  $v_f$ ,  $p_f$ , and n, the computer then randomly assigns a one-digit number to each feature value and feature price so that the two sums,  $v_f$  and  $p_f$ , are exactly met. Sellers can also re-randomize the computer's assignment of numbers as many times as they want until they are satisfied with how their products look. For example, if sellers believe that some buyers may not pay attention to all feature values and feature prices but will base their decision just on the base price and the first few add-on features, sellers may re-randomize until the first few features look particularly attractive (i.e., have high values and low prices).

We intentionally restricted the feature values and feature prices to single-digit numbers. This way, products are not overly complex. It would have been easy to introduce additional forms of obfuscation for example by allowing for random components in the feature's values, or making some add-ons complements or substitutes for each other. However, if we find that already our "mild" obfuscation opportunities enable the sellers' to appropriate substantial rents, then the more complex forms of naturally-occurring obfuscation opportunities can be expected to cause much worse outcomes for the consumers. In addition, the single digit constraint has the advantage that a product's degree of complexity can be easily summarized by the number of extra features. Finally, the single digit constraint can also be interpreted as a technological constraint that puts an upper bound on the value that each extra feature can provide. Such a constraint is quite plausible because it is generally not possible to generate arbitrarily high values without adding more features to a product.

To keep product complexity within limits, we also restricted the maximum number of features to 6. Furthermore, a seller of a product with  $n \ge 1$  features could maximally add an aggregate feature value  $v_f$  of up to 7n+2. This upper bound on the aggregate feature value automatically ensures that the single-digit constraint for individual extra features is met. To keep things simple, the sum of extra prices is subject to the same aggregate constraint. Note, that this design gives sellers the opportunity to make their products more complicated in terms of the number of add-on that are needed to generate the desired aggregate feature value  $v_f$ .

Thus, to summarize, each seller determines a base price  $p_b$ , the number of extra features n, the aggregate feature value  $v_f$ , the aggregate feature price  $p_f$ , and the presentation of the list of individual feature values and feature prices to the buyers. Before a seller commits to an offer in a given period, he or she

<sup>&</sup>lt;sup>6</sup> For example, a seller who wants to provide add-on features with an aggregate value of, say  $v_f = 29$ , can do so with 4, 5, or 6 extra features.

can try out many decisions; for each decision, the computer automatically calculates the overall cost of extra features  $c_f$ , earnings from extra features  $\pi_f^S$ , and profits per unit  $\pi^S$  to help the sellers fully understand the implications of their decisions.

Note that the extra features of the products in this experimental design are not any seller's unique technological innovations that provide *per se* a competitive advantage relative to the other seller's products. Rather, the possibility of adding extra features is a tool that can be used to generate additional value for the buyers, but all sellers have the same opportunities to produce these add-ons. In addition, the extra features are only vertically differentiated for the buyers because all buyers derive exactly the same value from a given extra feature with no uncertainty or noise. Thus, no buyer has a pre-determined taste or preference over certain types of products; rather, they just want to find the product that provides the highest monetary payoff  $\pi^B$ . Therefore, if competition is fully at work so that buyers choose only those products that give them the highest overall earnings  $\pi^B$ , the extra features should not enable sellers to earn positive profits.

After all the 6 sellers have determined their products for the current trading period, the "Buyer Stage" starts, in which all the 6 products are displayed to buyers, in an order that is completely randomized across periods. Because sellers do not have an ID and remain anonymous, and because all sellers and buyers know that the order of products in each period is randomly determined, our design eliminates any reputation concern. Sellers' reputation may of course play a role in naturally occurring markets with obfuscation opportunities, but reputation formation may interfere with obfuscation in multiple conflicting ways<sup>7</sup>. These confounds may make it hard to draw clean inferences about obfuscation behavior in the field, and most theoretical models of obfuscation also do not yet consider reputation formation. Therefore, here we are – as a first step – interested in how such a market operates in the absence of reputation formation opportunities.

### The Buyer Stage

At the beginning of the "Buyer Stage", each buyer is informed of their basic value in the current period, and then they can start shopping. When buyers are shopping, their time is valuable – for every second buyers spend in the market before they make a decision, they incur a cost of 0.1 ECU. On the screen (see Figure A1 in the Appendix for example screens), buyers first see only the base prices of the 6 products while the extra features of the various products are not immediately visible. However, the buyers have the opportunity to learn about the extra features of each product by "visiting" them.

To "visit" a product, a buyer has to click on the product on the screen. One click makes its first feature appear, the next click makes the next feature appear, and so on. Moreover, any product will only be clickable every 2 seconds. This design mimics typical situations of product search in that consumers usually always need time to find the next piece of useful information about a product; moreover, upon seeing a feature, consumers always need time to understand it and figure out its value. For this purpose, we actually consider the 2-second lag to be very conservative.

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<sup>&</sup>lt;sup>7</sup> For example, if buyers become averse to obfuscation, firms may avoid obfuscation for reputational reasons. Or if buyers have brand loyalty and keep buying a product without having to look through all the products in the market every time, it may also change the effect of any firm's obfuscation on other competitor firms and the market.

Moreover, only the features of the current product are visible; that is, when buyers switch the product they visit, the features of the previous product disappear. This design approximates the situation in which consumers do not always have access to convenient ways of displaying all the available information in front of them at the same time; rather, consumers usually have limited working memory about the complex products that they previously saw. Also, this design allows the experimenter to obtain a detailed dataset on which products buyers examine and each buyer's order and duration of each searched product. There is no limit on the total time that any buyer can spend in the market. In fact, the time cost of 0.1 ECU per second is also chosen in such a way that the buyers can acquire full information about all products and still earn a substantial profit.

### The Feedback Stage

After all buyers made their buying decisions, the trading period proceeds to the "Feedback Stage" (see Figure A2 in the Appendix for an example screen). In this stage, the sellers receive feedback on the details of the 6 products that were offered in the current period. For all offered products, sellers see the respective base prices, the extra features and their values and prices. In addition, they are informed about relevant summary statistics associated with each product: the aggregate feature value  $v_f$ , the aggregate feature price  $p_f$ , the aggregate feature cost  $c_f$ , earnings from extra features ( $p_f - c_f$ ), and profits per unit sold  $\pi^S$ . A seller also privately sees how many units he sold and his realized total earnings in the current period. The feedback for sellers provides them with substantial information about the whole market and thus may enhance competition.

Buyers, on the other hand, are shown their realized earnings from trading, total time cost, and total earnings in the current period.

### 2.2 The market without obfuscation

The whole experiment comprises 3 parts. In Part 1, participants interact in the OO market (market with obfuscation opportunities) described above for 20 trading periods. In Part 2, the same subjects participate in a control treatment – the NO market (market with no obfuscation). In this treatment, the participants have the same role assignments and interact with the same group of people under the same conditions as the OO market except that the computer provides information during the "Buyer Stage" that makes each product's overall net value immediately visible for each buyer.

Recall that the buyers' earnings from a trade  $\pi^B$  are given by,

$$\pi^B = \pi^B_b + \pi^B_f = (v_b - p_b) + (v_f - p_f) = v_b + (v_f - p_b - p_f).$$

<sup>8</sup> Nevertheless, as limitations in working memory are not the focus of the study, all the buyers are provided with paper, pen, and blank spaces on the shopping screen – so buyers have ways to record what they want to remember. 
<sup>9</sup> To mitigate "psychological liquidity constraints", we endowed each buyer with 8 ECU in every period. This endowment allows buyers to have enough liquidity to finance their search cost even if all 6 products have the maximal number of add-ons (i.e., 6) and the buyer wants to see them all; in this case the overall time costs are  $6 \times 6 \times 0.1 \times 2 = 7.2$  ECU.

Note that the buyers' basic values,  $v_b$ , which are randomly assigned and communicated to the buyers at the beginning of every period, do not affect the relative attractiveness of the different products because they refer to the value of a basic phone (which is identical across products). In contrast, the base price,  $p_b$ , the aggregate feature value,  $v_f$ , and the aggregate feature price,  $p_f$ , all depend on sellers' decisions. They typically vary across products and can be summarized by

$$v_o \equiv v_f - p_b - p_f$$
.

Therefore, the buyers only need to know the "overall net value"  $v_o$  to assess the relative attractiveness of the available products, and the computer publicly provides this information to the buyers in the NO market (see Figure A3 in the Appendix for an example screen). Because the NO market completely eliminates all the complexity and search cost created by add-on features, we conjectured that this market will relatively quickly converge to the competitive equilibrium in which the maximum surplus is produced and appropriated by the buyers. For this reason, the NO market lasted only 10 periods.

The NO market mimics an ideal form of policy intervention that requires all the sellers to summarize the useful information of their products in one quality-adjusted price (or in a way as simple as possible). For example, personal loan providers are required to summarize their products by just one Annual Percentage Rate (Ellison and Ellison, 2020). This treatment is virtually similar to the policy intervention proposed in Ellison (2005): sellers are required to advertise one price and provide all the add-ons free of charge<sup>10</sup>. This way, products' overall net values are also transparent to buyers.

### 2.3 Additional treatments

As mentioned above, the cost of producing the extra features is always 50% of the features' values in our main treatment. This means that extra features are uniformly surplus-enhancing as represented by the blue line in Figure 2 below. In this treatment, adding more feature values always increases both the available total surplus and complexity. While this type of obfuscation by producing surplus-enhancing add-ons likely approximates a frequently occurring form of obfuscation in naturally occurring environments (e.g. upgrades of products, extra accessories, faster shipping, etc.), we also want to understand how much obfuscation occurs in a competitive market when the surplus increases due to extra feature values are not all uniform and can become negative, so that more features do not always mean higher value. So, in addition to the treatment just described above - that we call "Half Cost Treatment (HCT)" – we implemented a second between-subjects treatment where the cost of producing extra features is a convex function of the values created, so that – beyond a certain level of  $v_f$  – adding additional feature values reduces the total surplus. We call this treatment "Convex Cost Treatment (CCT)"; it is represented in Figure 2 by the red line. In this treatment, the most efficient aggregate feature value is at 30 ECU, for which only 4 features are needed  $(4 \times 7 + 2 = 30)$ . That is, if sellers produce a higher level of feature values with more extra features than the most efficient level, the product becomes more complex but the total surplus is lower. By observing how complex sellers make their

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<sup>&</sup>lt;sup>10</sup> Ellison (2005) also shows theoretically that even when the add-ons are optional and consumers have heterogeneous preferences over add-ons, this policy intervention benefits both consumers who buy the add-on *and* consumers who do not buy the add-on.

products in this treatment, we are able to see whether sellers even want to produce inefficient extra features that merely complicate their products.

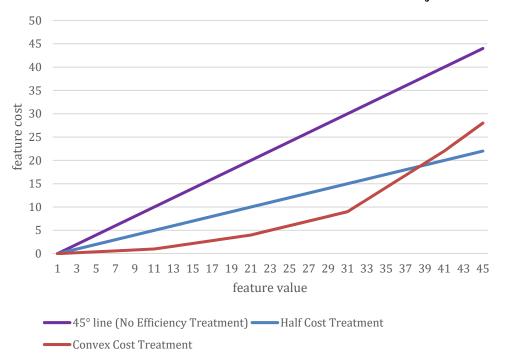


Figure 2: Feature cost as functions of feature value in the 3 between-subject treatments

Finally, we are also interested in the effects of purely "exploitative" obfuscation that only increases search costs, which has been frequently examined in theoretical work (Spiegler, 2006; Carlin, 2009; Ellison and Wolitzky, 2012; Chioveanu and Zhou, 2013). To study this question, we implement a third between-subject treatment called "Surplus-Neutral Treatment (SNT)" in which the production of feature values does not generate any additional surplus, i.e. the cost of producing any given feature value is equal to the feature value. Therefore, unlike the two previous treatments in which sellers may implement extra features in order to provide extra surplus, all the surplus in this treatment is already in the basic product, and sellers no longer need extra features to increase the surplus of their product. Experimentally, the total available surplus in this treatment is kept roughly identical to the actual surplus in the HCT and CCT<sup>11</sup> by moving all the surplus to buyers' basic values. Therefore, a seller who does not want to obfuscate can set  $v_f = 0$ ,  $p_f = 0$  and merely charge the base price without sacrificing any surplus. Adding extra features to the product in this treatment thus makes no sense unless the seller wants to make the product more complex for the sake of obfuscating the true value and price of the product. The SNT therefore enables us to explore whether obfuscation is maintained at a similar level compared to the other OO market treatments and how obfuscation for the mere sake of obfuscation affects the buyers' behaviors.

Note that the buyers in all of our treatments only know that sellers incur cost when they add extra features, but they are never informed about the sellers' cost levels. Therefore, any differences that may

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<sup>&</sup>lt;sup>11</sup> The total available surplus is 27 ECU in HCT, 26 ECU in CCT, and 25 ECU in NET.

arise in buyer behavior across these treatments cannot be due to their information about sellers' cost of providing add-ons.

The various treatments of our experiment are summarized by Table 1. In total, there are three betweensubject treatments times two within-subject treatments.

Table 1: Treatments in the current experiment

	Market with obfuscation opportunities (OO market)	Market with no obfuscation (NO market)
Half Cost Treatment (HCT)	6 markets	6 markets
Convex Cost Treatment (CCT)	5 markets	5 markets
Surplus-Neutral Treatment (SNT)	6 markets	6 markets

### 2.4 Additional tasks, procedures, and subjects

To better understand the mechanisms through which obfuscation influences buyers, we also elicit their beliefs about the aggregate net feature value  $(v_f - p_f)$  of products with different numbers of add-ons after the end of the 20 trading periods in the OO market. Buyers had to estimate the average aggregate net feature value of products in the market in which they just participated for each possible number of add-ons. They were rewarded 5 ECU for each estimate if it was within  $\pm 2$  ECU of the actual average aggregate net feature value. Their estimates will allow us to understand whether the buyers perceived more obfuscated products on average as more or less valuable. In addition, we also elicited buyers' beliefs about the average aggregate net feature value of products  $(v_f - p_f)$  at various base (i.e., headline) prices. We elicited this belief measure because buyers might make inferences about the aggregate net value of a product's add-on features based on the product's headline price.

At the end of the experiment, both buyers and sellers answer a short questionnaire that elicits their demographic characteristics. 10 random trading periods of the OO market, 5 random trading periods of the NO market, and earnings from Part 3 are paid out. This payment scheme alleviates House Money Effects – because subjects do not accrue earnings over time – and generates reasonable incentives to motivate subjects to make careful decisions in every period of the market at the same time.

The experiment was computerized and programmed with the experimental software z-Tree (Fischbacher, 1999). There are a total of 272 subjects. Each experimental session lasted approximately 2.5 hours and was held in the Econ Lab at the University of Zurich. Each subject earned on average 65 Swiss Francs (CHF 65  $\sim$  USD \$72) with an exchange rate of 7.11 ECU = 1 Swiss Franc ( $\sim$  US \$1.1). All subjects were recruited from the joint subject pool of the University of Zurich (UZH) and the Swiss Federal Institute of Technology Zurich (ETH). All interactions in the experiment were anonymous.

### 2.5 Discussion of potential outcomes

### No Obfuscation (NO) Market

Theoretically, sellers cannot escape the "zero-profit trap" in a market with Bertrand competition because as long as the lowest price is above marginal cost, a seller can undercut that price and serve the demands of the entire market, while all other sellers earn only zero profits. Experimental studies on Bertrand markets show that the Bertrand outcome will not be realized in the lab when there are only 2 or 3 sellers because of the possibility of implicit collusion. However, the Bertrand outcome is typically quickly reached when there are 4 or more sellers (Dufwenberg and Gneezy, 2000; Huck, Normann and Oechssler, 2004). Buyers in our NO market do not have pre-determined preferences for products with identical net values, and all buyers prefer products with higher net values. Competitive forces should therefore ensure that the buyers can realize the highest possible surplus, i.e. the market should provide the most efficient level of extra feature values, and total prices should just cover the sellers' costs. In this sense, the NO Market in our experiment is very similar to Bertrand competition. As we have six sellers, and each of whom can serve the whole market, we expect fierce competition in the NO market such that sellers produce the maximum possible surplus, which is appropriated by the buyers. This also means that the overall price that trading buyers pay for a product (i.e. the base price plus the aggregate feature price) is identical, i.e. the law of one price holds.

### Market with obfuscation opportunities (OO Market)

In a Bertrand market, consumers can easily compare the net values they derive from buying products from the various sellers. However, subjects may not be able to compare them easily in the presence of complex, obfuscated, products because they need to invest time and effort to understand each of the offered products. If sellers obfuscate, they thus generate endogenous search and comparison costs.

Diamond (1971) first formalized a model of markets with exogenous search costs and theoretically showed that monopoly pricing is an equilibrium in this environment. Intuitively, this result follows because in equilibrium, all consumers rationally expect all firms to charge monopoly prices and have, therefore, no incentive to search at all and just buy one of the products randomly. This consumer behavior, in turn, gives firms no incentive to lower their prices below the monopoly level. Similar monopoly pricing outcomes are predicted for products' hidden features in many theories of obfuscation and shrouded attributes under various other assumptions. For example, when consumers have similar degrees of price-insensitivity so that they all buy the add-ons (Ellison, 2005), or when myopic consumers totally ignore shrouded attributes and surcharges (Gabaix and Laibson, 2006; Heidhues, Kőszegi and Murooka, 2017), or when they have convex search cost so that they only search once in a highly obfuscated market (Ellison and Wolitzky, 2012), then add-ons are priced monopolistically.

However, when consumers have heterogeneous search costs, meaning that there are always some consumers who are willing to search, firms may face the incentive to undercut high add-on prices to attract the searching consumers. For example, the buyers in our OO market may have very different mental costs for searching and calculating the net values of the products, and this heterogeneity may act as a counterforce on the high pricing of add-on features. The motive to target those buyers who search by undercutting high prices of add-ons plus the motive to sell highly priced add-on features to buyers who do not search could also generate differentiation and dispersion in the add-on features in the market and lead to the violation of the "law of one price" (Carlin, 2009; Ellison and Wolitzky, 2012; Chioveanu

and Zhou, 2013). From the consumers' perspective, the differentiation and dispersion increases the expected gross benefit from searching and identifying better products, which may in turn make potential buyers more willing to search<sup>12</sup> and induce more sellers to undercut. In the end, the final price level is likely to depend on how much competitive pressure consumers exert on sellers with their search activities. In our experiment, we are able to explicitly examine the extent to which buyers search the market and how sellers respond to buyers' search activities. Moreover, we can measure the extent to which the sellers can in fact mitigate competition through obfuscation via add-ons by comparing the buyer surplus between the OO and the NO markets. In addition, we will be able to observe how price and add-on dispersion develops over time and whether stable dispersion patterns emerge.

Both in reality and in our experiment, the products' base prices are typically considerably more salient and transparent compared to the prices and values of the add-on features. Therefore, when consumers start to search in the market, the products' base ("headline") prices may guide their search. Choi, Dai and Kim (2017) apply Weitzman (1979)'s theory, according to which consumers' optimal search, *ceteris paribus*, should be in an ascending order of the headline prices<sup>13</sup>, which coincides with the intuition that consumers probably first examine the cheaper-looking products. This then means that base prices may be subject to stronger competition than add-on prices and may thus drop over time.

However, if base prices are positively correlated with the net values of add-ons, the buyers in our experiment may view low base prices as a noisy signal of high hidden prices (i.e. low aggregate net values) of add-on features, and this may then mitigate competition via headline prices.<sup>14</sup> This potential signaling function of headline prices may actually be important in markets with obfuscation opportunities because when buyers have a limited willingness to figure out the entire market, they may try to infer the hidden net values of add-on features from headline prices<sup>15</sup>. Because we can directly examine both buyers' search behavior as well as their beliefs about the aggregate net value of products' add-ons at different base prices, our data can shed light on these issues.

In many theoretical models of obfuscation, sellers can obfuscate without affecting the overall net value of the obfuscated products, which is the situation that we implemented in our Surplus-Neutral Treatment (SNT). In these models, obfuscation either generates search costs for consumers or confuses some consumers so that they buy products randomly. This in turn then allows firms to enforce prices above marginal cost, sometimes even monopoly prices. Thus, our Surplus-Neutral Treatment enables us to

<sup>&</sup>lt;sup>12</sup> The existence of dispersed prices, however, does not necessarily imply that consumers invest a lot in searching the market. In Ellison and Wolitzky (2012), for example, consumers' search is very limited because of convex search cost and a high degree of obfuscation by firms such that visiting another firm's product will be very costly. Therefore, they predict that individual firms' obfuscation can induce consumers to only search once and buy that product, even though there is price dispersion in the market. In our experimental setting (and perhaps in many natural-occurring markets), it may, however, be possible that more dispersion could lead some consumers to search more, which exerts competitive pressure on firms.

<sup>&</sup>lt;sup>13</sup> This result relies on the assumption that consumers believe that the distributions of the headline prices and the perceived distribution of hidden prices (i.e., prices of extra features in our setting) are independent. However, as we discuss below, this assumption may not hold.

<sup>&</sup>lt;sup>14</sup> Wolinsky (1983) shows, for example, that if only firms know the exact quality of products, the products' prices may serve as a signal of quality levels. In our set-up, limited search may lead to imperfect information about the net value of add-on features, and headline prices may be perceived as a signal of the net value of the add-ons. Heidhues, Kőszegi and Murooka (2017) also discussed the possibility that consumers may be suspicious of overly low headline prices.

<sup>&</sup>lt;sup>15</sup> For example, Völckner, Rühle and Spann (2012) provide evidence suggesting the existence of signaling effects when consumers are faced with partitioned prices.

examine the extent to which sellers can indeed enforce stable profits via obfuscation in such an environment. The treatment also gives us the chance to observe how buyers respond to this kind of obfuscation. In this context, it is important to mention again that the buyers in our experiment do not know whether add-ons are surplus neutral or surplus-enhancing. Buyers who search can only observe the prices and the values of the offered add-ons.

There is one aspect that did yet not receive much attention in the theoretical literature on obfuscation — the possibility that consumers may be averse to product obfuscation. Some literature (Gaudeul and Sugden, 2012; Crosetto and Gaudeul, 2012; Seim, Vitorino and Muir, 2017b; Chiles, 2017; Sugden and Zheng, 2018) has suggested that consumers appear to be averse to complexity and hidden fees, and that they value transparency. Complexity aversion may be the direct consequence of the search cost that complex, obfuscated products impose on consumers or it may result from consumers' experience that more complex products are, on average, more likely be associated with a "worse deal". For example, according to Carlin (2009) and Chioveanu and Zhou (2013), firms with worse products (i.e., products with higher prices) have a higher incentive to obfuscate. If firms' activities indeed lead to a negative correlation between a product's obfuscation level and its net value to consumers, then it appears natural that consumers will shy away from obfuscated products. If that were the case, systematic obfuscation may no longer be a stable outcome in a competitive market because firms that offer less obfuscated products may have a competitive advantage.

If add-ons do not increase the surplus associated with a product (i.e.,  $v_f = c_f$ ), firms can only benefit from add-ons by pricing them above their costs, which means that they charge more than the consumer is willing to pay for the add-on (i.e. by setting  $p_f > v_f = c_f$ ). However, if add-ons are not just a means of obfuscation but also increase the value buyers derive from the add-on ( $v_f > c_f$ ), both sellers and buyers can benefit from the increased surplus if firms set prices such that  $v_f > p_f > c_f$  holds. Thus, although the obfuscation-induced search process is costly for buyers, they will discover additional desirable features during the search that they are actually willing to pay for. Obfuscation via surplusenhancing add-ons may therefore counteract buyers' complexity aversion and may render obfuscation a stable outcome in competitive markets. By comparing buyers' behavior and obfuscation levels between the treatments in which the extra features are surplus-enhancing (Half Cost Treatment and Convex Cost Treatment) or not (Surplus-Neutral Treatment), we can examine whether this conjecture is true.

### 3 Results

In this section, we present our main results. We first focus on the two treatments with surplus enhancing add-on features (Half Cost Treatment and Convex Cost Treatment)<sup>18</sup>. We start by reporting the share and dispersion of the total surplus that buyers obtain in the OO Market and the NO Market in section 3.1. Then we decompose the share of the surplus that buyers fail to appropriate into (i) the component

<sup>&</sup>lt;sup>16</sup> Or more broadly speaking, extra features with prices higher than values also capture the general situation that consumers spend time comprehending the product, but they only find additional surcharges or bad attributes of the products that give them a negative aggregate net feature value.

<sup>&</sup>lt;sup>17</sup> In fact, Bertini and Wathieu (2008) show in an individual decision-making task that people react positively to a product when the surcharged add-on is perceived as a good deal.

<sup>&</sup>lt;sup>18</sup> We pool the data together for results where the two treatments differ only in irrelevant ways.

that they lose because sellers charge prices above marginal cost, (ii) efficiency losses due to the fact that sellers fail to choose the surplus maximizing level of feature values, and (iii) mistakes the buyers make because they fail to find the best product in the market. Then we examine the sellers' obfuscation strategies and the underlying intentions in more detail in section 3.2. In section 3.3, we analyze how sellers compete and are able to enforce positive profits by setting their base prices and the aggregate net value buyers derive from the products' add-on features. We investigate buyers' search and buying behavior and how a product's characteristics attracts or repulses buyers in section 3.4. Section 3.5 summarizes and decomposes the total welfare losses the buyers experience in the markets with surplusenhancing extra features. Finally, we study the extent to which our findings for markets with surplusenhancing extra features carry over to markets with surplus-neutral add-ons in section 3.6. This final section is of interest because almost all models of obfuscation assume that obfuscation takes a surplus-neutral form.

### 3.1 Buyer surplus and sellers' profits

Our first primary result concerns how much of the total surplus buyers obtain on average in the market with no obfuscation (NO Market) and in the market with obfuscation opportunities (OO Market), and the extent to which the buyer surplus that individual buyers earn is dispersed across buyers. We summarize the corresponding findings in

- **Result 1: (a)** In the absence of obfuscation opportunities, buyers receive almost all the surplus available in the market. After the first few periods, buyer surplus quickly converges to 97% of the total surplus.
  - **(b)** In contrast, buyers get a much smaller share of total surplus, initially as low as 11%, in the presence of obfuscation opportunities. Buyer surplus converges towards roughly 2/3 of the total surplus in the long run.
  - **(c)** Dispersion in individual buyers' buyer surplus quickly becomes negligible in the NO Market, whereas large and stable dispersion always prevails in the OO Market, indicating a violation of the law of one price.

We document Result 1 in terms of the share of the traded buyer surplus that buyers obtain on average in the market in percent of the maximally possible total surplus. Recall that buyers' earnings from a product are  $\pi^B = (v_b - p_b) + (v_f - p_f)$ . If we denote the aggregate feature value  $v_f$  that maximizes the total surplus from feature values by  $v_f^{max} \equiv argmax [v_f - c_f(v_f)]$ , the percentage of the total available surplus a buyer receives from a trade is given by

$$\frac{\pi^B}{\pi^B + \pi^S} = \frac{(v_b - p_b) + (v_f - p_f)}{(v_b - c_b) + (v_f^{max} - c_f(v_f^{max}))}$$

If at least one seller in the market provides the efficient level of extra features  $v_f^{max}$  and prices his/her product at marginal cost (i.e.,  $p_b + p_f = c_b + c_f(v_f^{max})$ ), then any buyer who buys this product earns the maximum possible surplus.

Figure 3 shows the average buyer surplus per trade in percent of the maximum possible total surplus over the course of the experiment in the NO and the OO markets. <sup>19</sup> In addition, the figure displays the within-period market-level dispersion in buyer surplus with "deviation bars" that indicate plus/minus one standard deviation of the buyer surplus from the mean. In the NO market, where all obfuscation is removed by design, the average traded buyer surplus starts off at a very high level (83%), quickly increases to 94% in period 3, and finally reaches on average 97% of the total surplus in periods 6-10. In addition, the dispersion of the buyer surplus very quickly becomes extremely small. It appears that the main reason why the buyer surplus does not reach 100% is that sellers shy away from prices that give them literally zero profits, i.e., sellers want to earn at least one ECU from their trade. However, apart from this small friction, competition pushes the total surplus to its most efficient level and prices very close to marginal cost in the NO Market such that the law of one (overall) price holds.

 $\infty$  $\infty$ buyer surplus per trade 2 .4 .6 4 2 0 0 5 10 0 15 20 period avg traded in NO Market +-1 standard deviation avg traded in OO Market +-1 standard deviation

Figure 3: Average buyer surplus per trade as a share of the maximally possible surplus in NO Market and OO Market

Notes: The figure shows the average buyer surplus per trade (plus/minus one standard deviation) as a percentage of the maximum possible total surplus across the 20 periods in the market without obfuscation (NO Market) and the market with obfuscation (OO Market). The figure is based on the pooled data from the Half-Cost Treatment and the Convex Cost Treatment. The traded buyer surplus in the OO market is significantly lower than the buyer surplus in the NO market (p = 0.000, t test).

In contrast, Figure 3 shows that the buyer surplus in the market with obfuscation opportunities (OO Market) is only 11% of the maximum total surplus at the beginning, implying that sellers appropriate

<sup>19</sup> In the OO markets it sometimes happened that not all buyers trade. Because buyers have different values for the basic product, some variations in the actual average surplus per trade may merely reflect which buyers failed to trade. To correct for this variation, we used the average base value (where the average is taken across *all* buyers) to calculate the buyers' surplus share in Figure 3. This ensures that the reported surplus share in Figure 3 only reflects variations in offered and traded products and is not affected by individual traders' base values. Note also that this means that Figure 3 does *not* include the buyer surplus that is lost due to non-trades in the OO Market.

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the lion's share of the total surplus. Competition pushes the buyer surplus up over time, and the buyers' share stabilizes at roughly 2/3 of the total surplus from period 13 onwards. The buyers' share of the surplus in the OO market is thus significantly lower than the buyers' share in the NO market (p = 0.000, t-test with standard errors clustered at the market level<sup>20</sup>). In addition, there is a large and stable spread in the buyers' surplus throughout the whole 20 periods: the within-period standard deviation of individual buyers' share in the total surplus is roughly 13 percentage points and does not differ between the first 15 and the last 5 periods (p = 0.862). The mirror image of these facts is, of course, that sellers earn a substantial share of the total surplus in the OO Markets, and that their individual shares per trade are also quite dispersed.

Why do buyers only end up with such a low level of buyer surplus in the market with obfuscation opportunities? Is it because sellers fail to provide the efficient level of extra features, or do sellers implement efficient extra features but charge high prices? Or is it because buyers do not identify the best offered product that is available in the market? The next result answers these questions.

**Result 2:** In the market with obfuscation opportunities, the sellers can prevent buyers from appropriating the total surplus mainly by (i) enforcing high prices and (ii) buyers' failure to purchase the best available product in the market. In contrast, the buyer surplus loss due to (iii) inefficient levels of feature values is small.

Figure 4 shows the decomposition of the buyers' surplus loss in the OO Market described in Result 2. The figure displays the average traded *buyer surplus* (the circle line), together with the average *total* surplus (the triangle line) and the average buyer surplus (the square line) provided by the best offer in the market. All three graphs are normalized by the maximum possible total surplus so the scale of the vertical axis is the same as Figure 3. The best offer is defined by the product in the market that gives the buyers the highest surplus. Thus, the triangle line shows the extent to which the best offer in the market generates the maximal total surplus by implementing the efficient level of extra features. The difference between the total surplus and the buyer surplus in the best offered product in the market shows the share of the surplus that the sellers of the best offered products could appropriate. The difference between the buyer surplus in the best offered product and the average traded buyer surplus in a period informs us about the extent to which buyers did not identify the best offered product in the market, and instead bought an inferior product.

Figure 4 nicely illustrates all three regularities described in Result 2. First, the big gap between the square line and the triangle line indicates that even sellers who make the best offers to buyers earn substantial profits. In other words, even the best offered product among the 6 competing products retains a price substantially above marginal cost. In Periods 16-20, the buyer surplus offered in the best available product stabilizes at only 80%, significantly lower than the maximal buyer surplus (p = 0.000).

Second, unlike in the NO market, the best offered product no longer solely determines how much surplus buyers obtain; the difference between the average traded buyer surplus (the circle line) and the buyer surplus in the best available product (square line) shows a stable level of buyer error in identifying the best offered product across the entire 20 periods (p = 0.000). Consequently, this failure to identify the

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<sup>&</sup>lt;sup>20</sup> All our statistical results in the paper are based on t-tests that cluster standard errors at the market level unless specified otherwise.

best product amounts to another loss in buyer surplus of around 12%. Sellers appropriate reductions in buyer surplus from both high prices and buyer mistakes, allowing them to earn around 32% of the total surplus in the long run (i.e., periods 16-20).

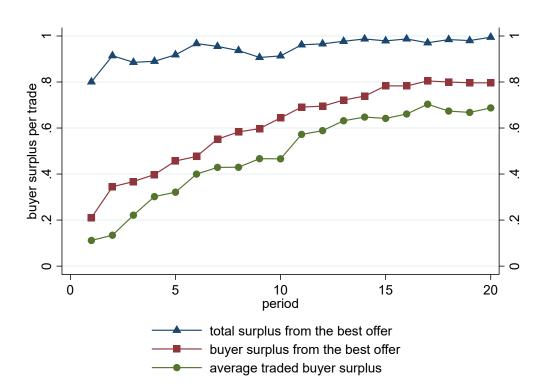


Figure 4: Decomposition of buyer surplus loss in markets with obfuscation opportunities (OO Markets)

*Notes:* The figure shows the average buyer surplus in traded products, the buyer surplus buyers could earn if they identify and buy the best offer in the market, and the total surplus generated by the best offer (product) in the OO market. The figure is based on the pooled data from the Half-Cost Treatment and the Convex Cost Treatment, and all graphs are displayed as a percentage of the maximum possible total surplus. The buyer surplus from the best offer is significantly lower than its total surplus (p = 0.000), and the average traded buyer surplus is also significantly lower than the buyer surplus from the best offer (p = 0.000).

Third, the loss of total surplus from the best offered product due to inefficient levels of feature values, as represented by the difference between 100% and the triangle line, is rather small and negligible in the last 10 periods. That is, the best offered product in the market relatively quickly implements the efficient level of feature values.

Taken together, while seller earn close to zero profits in the NO Markets, the results for the OO Markets indicate that sellers successfully escape the "zero-profit trap" when there are obfuscation opportunities; none of the sellers in the OO Markets price the product at marginal cost, and even sellers who offer inferior products have a fair chance of selling their product because buyers often do not identify the best product in the market. Thus, Results 1 and 2 show that the existence of obfuscation opportunities causes higher prices and a lower buyer surplus. These results also suggest that policy interventions similar to the one we implemented in NO Markets – summarizing products in the simplest form possible or standardizing free add-on provision to enforce competition with one price – may be very effective in enforcing competition and increasing buyer surplus.

### 3.2 Sellers' obfuscation strategies

Why does the existence of obfuscation opportunities enable sellers to reap positive profits and reduce the buyers' share of the total surplus? The answer likely depends on whether and how sellers make use of the obfuscation opportunities. Our next result summarizes our empirical findings in this regard.

- **Result 3:** (a) Obfuscation opportunities are widely used in the OO Markets. Sellers add more add-on features on average than what would be required to generate their desired level of feature values.
  - **(b)** In addition, sellers intentionally manipulate the order of add-on features so that those features that first become visible are most attractive for the buyers, while the least attractive add-on features only become visible through deeper search.

We provide support for Result 3a in Figures 5 and 6. Figure 5 shows the average complexity of both offered and traded products in the Half Cost Treatment (HCT) and the Convex Cost Treatment (CCT), respectively. The average number of offered add-on features per product is 5.4 in HCT and 4.7 in CCT in periods 11-20. The complexity of average traded products is not less than the complexity of the average offered products; if anything, complexity is even slightly higher in the average traded products (p = 0.095 in HCT and p = 0.463 in CCT). That is, buyers buy products with average (or higher) complexity from the set of offered products and do not show an obvious preference for simple products.

Recall that the efficient aggregate feature value in the Half Cost Treatment requires 6 add-ons, while efficiency only requires 4 add-ons in the Convex Cost Treatment. However, the average offered product complexity is at a stable level significantly above 4 (p = 0.009) in the Convex Cost Treatment, meaning that many sellers are willing to obfuscate by adding too many features relative to the surplus-maximizing level. Another notable pattern is that offered complexity in the Half Cost Treatment is significantly higher than in Convex Cost Treatment (p = 0.006). This suggests that the fact that add-on features are surplus-enhancing over a wider range in the Half Cost Treatment facilitates obfuscation in that treatment. More implications of surplus enhancing add-on features will be discussed in the section where we present the results of the Surplus-Neutral Treatment.

When add-on features are surplus-enhancing, one may wonder whether the high complexity level in the market is just a consequence of the desire to improve a product's competitive position by increasing its total surplus. There are, however, three pieces of evidence that contradict this view. First, sellers in the Convex Cost Treatment over-obfuscate on average relative to the surplus-maximizing aggregate feature value. Second, sellers also typically over-obfuscate relative to the minimum number of add-on features required to implement their desired level of aggregate feature values. This is illustrated in Figure 6. In this figure, the horizontal axis categorizes all the offered products according to how many features sellers minimally need to produce their desired aggregate feature value, while the vertical axis gives the actual average number of features that these products have. For example, the solid circle at minimally needed complexity =1 in Figure 6 contains all those products that have an aggregate feature value of 9 or less; this means that only 1 add-on feature is needed to produce the aggregate feature value. However, Figure 6 shows that the actual number of features for these products is on average 4.6, which is significantly above 1. In fact, all the offered products with a minimally required feature number of 5 or less are significantly more complicated than needed to produce the desired aggregate level of feature value. This follows from the fact that the 95% confidence intervals for these product categories never

intersect with the 45-degree line. This systematic over-obfuscation points towards motives other than merely increasing surplus via add-on features.

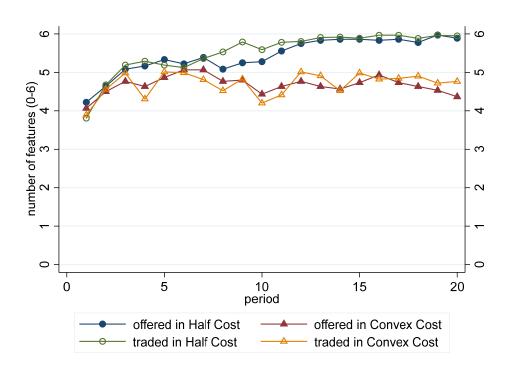


Figure 5: Product complexity in the Half Cost Treatment (HCT) and the Convex Cost Treatment (CCT) of markets with obfuscation opportunities (OO Markets)

*Notes:* The figure shows the average number of features in both the offered and traded products in the OO market. The figure presents data from the Half-Cost Treatment and the Convex Cost Treatment separately. The average offered product complexity in CCT is at a stable level significantly above 4 (p = 0.009), but is significantly below the average offered product complexity in HCT (p = 0.006).

The third piece of evidence supporting that sellers' intentionally try to obfuscate is provided in Figure 7. Recall that sellers only determine the aggregate feature value and the aggregate feature price of their product, while the computer determines the values and prices of individual features randomly. If sellers are not satisfied with one realization, they can re-randomize until they are satisfied. And we find that they indeed use this re-randomization opportunity very frequently. On average, each seller re-randomized the display of the extra features between 3-4 times per period, and some sellers even re-randomize several dozens of times.

If each of the individual feature values and prices were really randomly determined across the display positions of features (see Figure 1), then across all the offered products, there should be on average no difference in the net feature value  $v_f^i$  -  $p_f^i$  across the display position i of individual extra features. That is, the average net value of the features shown at the top of the feature list should be the same as the average net value of the next shown features, and so on.

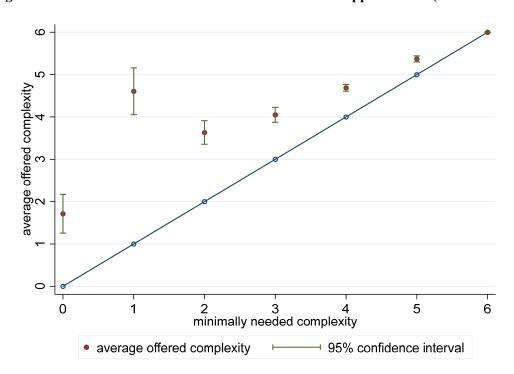


Figure 6: Over-obfuscation in markets with obfuscation opportunities (OO Markets)

*Notes:* The figure shows the average complexity of offered products (together with the associated 95% confidence interval) compared to the minimal complexity needed to generate the offers' intended feature values. The figure is based on the pooled data from the Half-Cost Treatment and the Convex Cost Treatment.

Figure 7 depicts the average net value of features on the y-axis across display positions of features on the x-axis. The figure shows that at any position of the display order, that position's feature is on average significantly more attractive than the next position's feature<sup>21</sup> (p = 0.001 from a joint clustered t test between features in one position and in the next position). This pattern is particularly pronounced among the first three feature positions. Thus, if buyers do not inspect all features of a product, they will only see a first few attractive features and remain ignorant about the product's less attractive features. In fact, we will provide direct evidence for such a search pattern among buyers in Result 7 – a pattern that provides incentives for the sellers to make the first few features more attractive than the downstream features. This display behavior of the sellers supports Result 3b and suggests that sellers intentionally distorted the display order in a way that improves the appearance of their product to imperfectly informed buyers. The sellers seem to anticipate the buyer's search patterns and optimize the appearance of their products accordingly.

<sup>21</sup> Only the last 2 features are not significantly different from each other; but this may simply result from the fact that, by design, sellers can determine the display order only by letting the computer re-randomize the whole order so that they do not have full control over the attractiveness of each extra feature.

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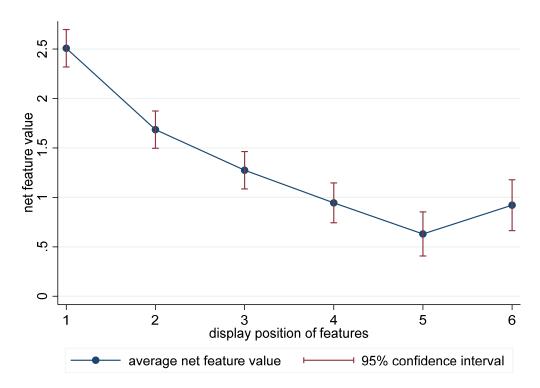


Figure 7: Net feature values across display positions of add-on features

*Notes:* The figure shows the average net feature value (i.e., feature value – feature price) of individual add-ons in offered products across display positions of individual features within a product. The associated 95% confidence intervals are also presented. The figure is based on the pooled data from the Half-Cost Treatment and the Convex Cost Treatment. A joint t-test for whether the net feature value of each feature is higher than its next feature yields a p-value of 0.001. The first 4 features are also individually significantly (at least at a 10% level) different from each other (p = 0.001 between the first and the second feature, p = 0.072 between the second and the third feature, and p = 0.016 between the third and the fourth feature).

### 3.3 How do sellers compete and earn profit?

As sellers make ample use of the obfuscation opportunity offered in the OO Market, the crucial next question is how obfuscation helps sellers make profits. As a product's overall price consists of a base price, which is transparent and costless for the buyers to see, and individual feature prices, which are only visible at some small cost, sellers' profits could come from two sources: (i) base prices higher than marginal costs of basic products and (ii) aggregate feature prices higher than aggregate feature costs. Many models in the theoretical literature (e.g., Ellison 2005; Choi, Dai and Kim 2017; etc.) have conjectured that headline prices may serve as an attention-grabber in an add-on pricing setting and may, therefore, be set at low levels in order to attract consumers. Once consumers have been lured to visit a firm's store or website, they may have a limited willingness to switch to competing firms, meaning that the visited firm can earn profits from its add-on features. However, as low base prices may also be a signal for high priced add-on features, it is not obvious whether this theoretical conjecture will hold empirically. In addition, because of the difficulty of identifying firms' production costs and profits from their basic products and add-ons in the field, there has been scarce evidence regarding profits from basic products and profits from add-on features, especially on the market level. Our next result fills this gap by precisely documenting the sources of sellers' profits.

**Result 4: (a)** Initially, base prices are considerably above marginal cost but they fall rapidly over time and many sellers offer and many trades take place at base prices below marginal cost from Period 11 onwards.

- **(b)** Low headline prices do not signal add-ons with low values for the buyers.
- (c) Sellers are able to enforce aggregate feature prices substantially and persistently above aggregate feature costs. Therefore, add-on features constitute the main source of profits that obfuscation enables.

Results 4 suggests that headline prices are subject to intense competition over time such that sellers even incur losses on their basic products, while the obfuscated extra features eventually become the key source of profits. Support for Result 4a comes from Figure 8, which shows the average base prices across OO markets. In addition, the figure shows the flat marginal cost curve and the buyers' valuations for the basic product. The figure illustrates that base prices are initially far above marginal cost but drop quickly and eventually fall even significantly below marginal costs from period 11 onwards (p = 0.020 from a t-test clustered at market level between all base prices in periods 11-20 and the marginal cost). Figure 8 raises, of course, the question why base prices fall so sharply, and how this is related to buyers' search behavior. For example, if buyers had a strong incentive to visit products with low base prices, then sellers would have a strong incentive to compete via base prices. A first hint in that direction is provided by the fact that the base price of the traded products is typically below the price of the offered products, indicating that low base prices seem to attract buyers. We deal with this question in more depth in the next section that discusses buyers' behavior.

We previously discussed the possibility that low headline prices may indicate that sellers are providing "hidden" overpriced add-ons. If this were the case, buyers might become suspicious of products with low headline prices, which would constrain sellers' ability to lure buyers into buying products with overpriced add-ons. Result 4b shows, however, that low headline prices do not indicate a lower overall net value of add-ons for the buyers. We illustrate Result 4b with Figure 9, which depicts the products' aggregate net feature values (i.e., aggregate feature values – aggregate feature prices) across different headline prices. There is considerable variation in the aggregate net feature values for each given headline price as indicated by the box plots, and the relationship is overall rather flat<sup>22</sup>. However, if we regress the products' aggregate net feature values on headline prices (while controlling for period dummies), we even find a slightly negative relationship: a reduction in the headline price by one unit increases the product's aggregate net feature value by 0.43 units (p = 0.024). This means that buyers had little reason to be suspicious of low headline prices because sellers who offered low prices also offered, on average, better add-ons although buyers might have had difficulty detecting this due to the noisiness of this relationship.

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<sup>&</sup>lt;sup>22</sup> Belief data also show that buyers' estimate of this relationship is also roughly flat, which is consistent with the true relationship depicted in Figure 9.

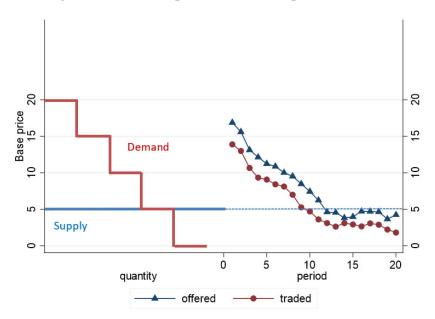


Figure 8: The development of headline prices over time

*Notes:* The figure shows the constant marginal cost of the basic product (blue thick line in the left part of the figure), the buyers' valuations of the basic product (red thick line in the left part), and how the prices of the offered and traded basic products evolve over time (in the right part of the figure). The figure is based on the pooled data from the Half-Cost Treatment and the Convex Cost Treatment. From Period 11 onwards, the average traded base prices are significantly lower than the marginal cost (p = 0.020).

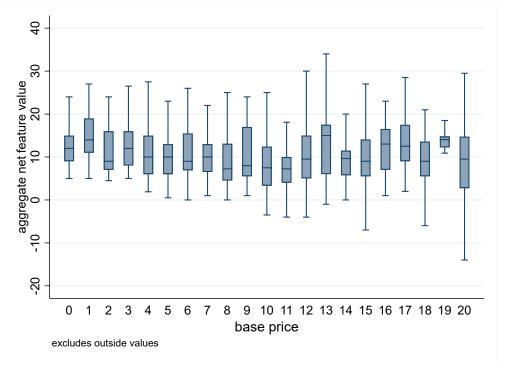


Figure 9: The relation between products' aggregate net feature values and their base prices

*Notes*. The figure shows the box plot of net feature value, which contains its median and its interquartile range (that contains 50% of the observations) for any feasible base price. The endpoints of the aggregate net feature values (for any given base price) indicate the median plus/minus 1.5 times the interquartile range. The figure is based on the pooled data from the Half-Cost Treatment and the Convex Cost Treatment.

If sellers incur losses from their basic products but still earn positive overall profits in the long run, then the extra features must be the source of the profits. Figures 10(a) and 10(b) illustrate this observation by showing how the average aggregate feature values, prices, and costs evolve over time in offered and traded products respectively. While the aggregate feature value and the aggregate feature costs only reflect sellers' design of their products – and indicate that sellers generate a substantial surplus via their add-on choices – aggregate feature prices turn out to be substantially and significantly higher than the aggregate feature costs (p < 0.001). Recall that the same technology to produce add-ons is available to all the sellers and that the products are only differentiated vertically. Therefore, the extra features are highly replicable and, if competition is fully at work, they should not have prices above their marginal costs. However, sellers are able to obtain a sizable and stable share of profits over the entire 20 periods. Notice that this also means that the increase of the buyer surplus over time in the OO Markets (see Figure 3 and 4) stems almost entirely from declining base prices.

A comparison of Figures 10a and 10b also reveals that the average buyer surplus from add-ons in traded products (Fig. 10b) is only slightly higher (by 7% of the maximal total surplus) than the buyer surplus that sellers offer on average (Fig. 10a). Thus, buyers are on average not able to find products with much better extra features compared to the average in the market. This is in line with the observation in Figure 4 that a significant share of buyers is unable to identify the best available offer in the market, meaning that inferior products also have a chance to be traded.

(a) Offered products (b) Traded products trades 25 30 Average t 15 20 2 period period aggregate feature costs aggregate feature values aggregate feature costs aggregate feature values aggregate feature prices aggregate feature prices

Figure 10: Aggregate feature values, feature prices and feature costs

*Notes:* The figure shows the aggregate feature values and the associated aggregate feature costs in offered (a) and traded (b) products. The difference between aggregate feature values and aggregate feature costs is a measure of the surplus the extra features provide. The aggregate feature price (line with circles) shows how this surplus is distributed between buyers and sellers. The figures are based on the pooled data from the Half Cost Treatment and the Convex Cost Treatment. The figure documents that sellers appropriate a stable share of the surplus generated by the products' extra features. The aggregate feature price of offered (traded) products is significantly higher than the aggregate feature cost of offered (traded) products). The aggregate feature value of offered (traded) products is significantly higher than the aggregate feature price of offered (traded) products (p < 0.001 for offered and traded products).

### 3.4 Buyers' search and buying behavior

In naturally occurring markets, the complexities generated by add-ons and the fact that it takes time to find, assess, understand, and evaluate them imposes "search" costs on consumers. We mimic some of these aspects in our experiment by making the products' add-ons not immediately visible to the buyers, but allowing them to become better informed by investing time and effort. We thus expect the buyers to spend time searching, and our next result summarizes the buyers' search behavior, which reflects how obfuscation influences buyers directly.

- **Result 5: (a)** Buyers spend a fair amount of time examining the available products in the OO Market, while product search is almost absent in the NO Market. Over time, product search declines but remains significant in the OO Market, constituting an efficiency loss in the market.
  - **(b)** Buyers' search behavior in the OO Market is rather incomplete. On average, buyers visit less than 50% of the products and view only 54% of the add-ons in the visited products.
  - (c) Buyers visit products with low (but not the lowest) base prices with a much higher probability first.

Figure 11a illustrates Result 5a. The figure plots the average time buyers spent searching in the NO Market and OO Market separately for the Half Cost and the Convex Cost Treatments because – according to Result 3 – the obfuscation levels differ between these two treatments. While time spent in the NO Markets is almost 0, buyers spend, on average, significantly more time on search in the OO Markets (p = 0.000). Initially, search costs are particularly high in the Half Cost Treatment of the OO market, but they quickly decline and converge in both treatments to slightly above 20 seconds after period 10.

Figures 11b and 11c provide support for Result 5b. Figure 11b plots the average number of visited products per period across the 20 periods, both including and excluding the case where buyers visited the same product repeatedly. The figure shows that buyers almost always visit fewer than 3 of the 6 available products in the market on average, i.e. they remained completely uninformed about the characteristics of more than half of the products in the market. Figure 11c depicts the average percentage of add-ons that buyers investigate for those products that they actually visited, and shows that more than 40% of the information about the add-ons of visited products is never taken up<sup>23</sup>. This figure therefore rationalizes Result 3, which shows that sellers spend effort to intentionally manipulate the display order of the add-on features by positioning the more attractive features higher up on the feature list.

As buyers visit only a limited number of products in the market, it becomes particularly important to attract buyers' as soon as possible, i.e. during the first few searches. We examine how base prices attract buyers in Figure 11d, which shows the average base prices of buyers' first visited products, along with

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<sup>&</sup>lt;sup>23</sup> Heidhues, Johnen and Koszegi (2020) discuss a related problem of consumers with limited attention/search – how the trade-off between superficially "browsing" over several products versus the "in-depth study" of a very limited number of products affects behavior in competitive markets. They assume that consumers are exogenously restricted to attend to only two pieces of price information – either the base price of two products (= browsing) or the base price and the add-on price of one product (= in-depth study of one product). This "imperfect attention" assumption implies that companies face quite limited competitive pressure. While our setting is slightly different – because buyers simultaneously see all headline prices – our results indicate that buyers typically prefer an "interior solution" to the "browsing" versus "in-depth study" problem: they only partially visit the various products ("browsing", Figure 11b), and they only partially examine the add-on space of the products they visit (Figure 11c). Taken together, this search pattern of the buyers endogenously generates limited competition in the add-on space.

the minimum and the maximum base price in every period. We see that buyers apparently first visited products with relatively low base prices, but not the product with exactly the lowest base price (p = 0.000). This constitutes direct evidence of the attention-grabbing effect of low headline prices, but it also suggests that some buyer suspicion is indeed present with regard to the products with the lowest base prices in a period.

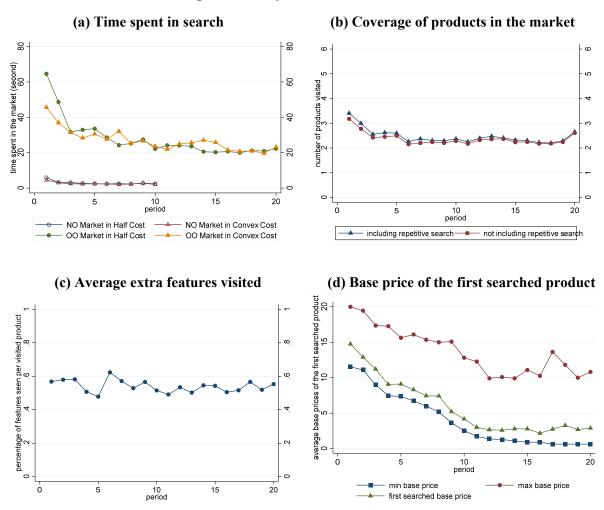


Figure 11: Buyers' search behavior

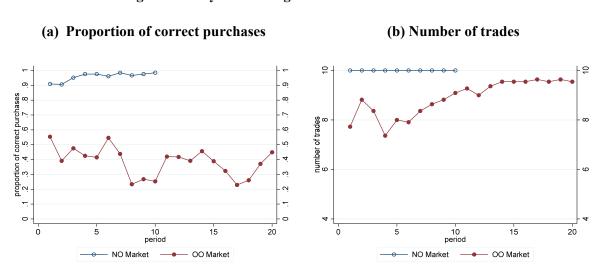
*Notes.* Figure (a) shows the average time buyers spend in searching the OO market and the NO market for the Half-Cost Treatment and the Convex Cost Treatment separately. Figure (b) illustrates the average number of products that buyers visit in the OO market; we show the case where buyers repeatedly visited the same product separately. Figure (c) shows the percentage of add-ons the buyers collected information about when they visited a product. Figure (d) shows the average base price of buyers' first visited products together with the range of base prices across different periods. Figures (b), (c). and (d) are based on the pooled data from the Half-Cost Treatment and the Convex Cost Treatment. In Figure (d), the average base price of the first searched products is higher than the lowest base prices in the market with p = 0.000.

This incomplete buyer search almost inevitably implies mistakes in buying behavior. Buyers may fail to find and buy the best available product in the market, and they may sometimes even fail to trade. Our next result summarizes the evidence with regard to buyers' mistakes.

**Result 6:** In the market with obfuscation opportunities, more than half of the buyers typically fail to buy the best available product in the market. Buyers sometimes even do not trade and thus completely forgo the available gains from trade. This contrasts sharply with the NO market where all buyers always trade, and almost always buy the best available product.

Figures 12a and 12b support this result. Figure 12a shows the proportion of buyers who end up buying the best product in the market, and Figure 12b displays the number of trades that take place in every period. While buyers in the NO Market almost always buy the best product in the market and everybody trades, more than half of the buyers in OO Market usually do not end up with the best products (p = 0.000). Moreover, failure to trade is around 20% during the first 6 periods. Although the percentage of non-trades diminishes to less than 5% during the final periods, it is still non-negligible for about 12-13 periods, and significantly positive across the entire 20 periods (p = 0.000). These buyer mistakes are an important reason why sellers only faced limited competitive pressure; sellers who offered inferior products were still able to sell them, and sellers with the best product in the market may sometimes not even have been able to trade at all or traded less than what would have maximized buyers' welfare and total efficiency.

Figure 12: Buyers' trading mistakes and failures to trade



Notes: Figure (a) shows the proportion of buyers who managed to buy the best available product in the market. Figure (b) shows the number of buyers who traded among the 10 buyers in the market. Both Figures (a) and (b) are based on the pooled data from the Half-Cost Treatment and the Convex Cost Treatment. The proportion of buyers who are able to buy the best product in the NO Market is lower than in the OO Market with p = 0.000. The number of trades that occur in the NO Market is also lower than in the OO market with p = 0.000.

Our previous results suggest that sellers' obfuscation activities are associated with incomplete buyer search, to which sellers responded by competing fiercely with their salient headline prices. At the same time, sellers were able to appropriate a large share of the surplus that they produced via add-ons by overpricing them relative to their cost. This seller behavior is rational if buyers, ceteris paribus, respond very elastically to a sellers' and his competitors' headline prices but relatively inelastically to the seller's and his competitors' aggregate feature prices. Our next result summarizes our findings in this regard:

**Result 7: (a)** Sellers can substantially increase their sales by decreasing their base prices. Likewise, the base price of the best product also has a sizeable impact on other sellers' sales.

**(b)** The aggregate values and prices of a product's extra features exert a considerably smaller effect on the product's sales. Likewise, the impact of the aggregate value and aggregate price of the best product's extra features on other products' sales is relatively small.

Table 2 reports OLS regressions of products' sales on the characteristics of the product itself and the characteristics of the best available competing product in the market with two regression specifications. The regressions also control for market complexity (i.e. the average number of extra features) and time trend; standard errors are clustered on the market level. It turns out that base price variations exert the largest impact on a product's sales: lowering the base price by 10 ECUs significantly increases sales by around 1.6-1.8 units<sup>24</sup>. Similarly, both the base price of the best available product in the market (column 1) and the lowest base price among the competing products in the market (column 2) play a similar (although slightly smaller) role: a reduction in the best competitor's base price (or a reduction in the lowest base price among the competitors) significantly lowers a seller's sales. This large buyer response to base prices helps us understand why sellers competed so fiercely with their headline prices that they even lowered them below marginal cost.

The high elasticity of buyers' behavior to headline prices contrasts with their much lower elasticity to the aggregate feature values and aggregate feature prices: an increase in aggregate feature prices by 10 ECUs reduces a product's sales only between 0.4 - 0.6 units. Likewise, an increase in aggregate feature values by 10 ECUs increases a product's sales only between 0.6 - 0.7 units. The difference in buyers' responsiveness to headline prices versus the aggregate features values and prices is highly significant (p =  $0.000^{25}$ ). Furthermore, the aggregate feature values and prices of the best competing product in the market have similarly small impacts on the seller's own sales<sup>26</sup>; and the best aggregate feature value or the best aggregate feature price among the competitors basically does not matter at all<sup>27</sup>. It is worthwhile to contrast these sluggish buyer responses to the products and the competitors' aggregate feature values and prices with our findings in the NO Market. The best available product in that market attracts almost all the buyers, practically eliminating the sales of competing sellers, while competition is strongly reduced and inferior products have a good chance of being sold in markets with obfuscation opportunities.

We have seen in Result 5 that buyers typically do not examine all of the add-ons of a visited product. In fact, they tend to neglect roughly 40% of the add-on features of visited products. This result appears to lend support to theories of obfuscation (e.g., Gabaix and Laibson, 2006; Heidhues, Kőszegi and Murooka, 2017) that assume that consumers ignore or oversee the surcharge imposed on the shrouded attributes. However, the regressions above indicate that a product's aggregate feature values and feature prices exert a small influence on buyer behavior, suggesting that they do not completely ignore them. To shed further light on this issue, we also asked the buyers in our experiment after every trade (but before they received the feedback screen) to provide an estimate of the overall net value of the *product they just bought*. It turns out that the buyers initially make considerable mistakes in the form of

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 $<sup>^{25}</sup>$  In both regression specifications, p = 0.000 for the hypothesis that the (absolute value of the) coefficient of the product's base price equals the coefficient of aggregate feature value and for the hypothesis that the coefficient of the product's base price equals the coefficient of aggregate feature price.

 $<sup>^{26}</sup>$  p = 0.003 for the hypothesis that the (absolute value of the) coefficient of the product's base price equals the coefficient of the best competitor's aggregate feature value and p = 0.000 for the hypothesis that the coefficient of the product's base price equals the coefficient of the best competitor's aggregate feature price. p = 0.045 between the best competitor's base price vs. best competitor's aggregate feature value, and p = 0.001 between the best competitor's base price vs. best competitor's aggregate feature price.

 $<sup>^{27}</sup>$  p = 0.000 between the product's base price vs. best feature value and between the product's base price vs. best feature price. p = 0.047 between the best base price vs. best feature value and p = 0.044 between the best base price vs. best feature price.

overestimating the overall net value, but that they were on average on target from period 11 onwards (p = 0.798). Thus, despite the fact that buyers did not examine all features of the products they visited, they acquired a reasonable estimate of the overall net values of the products they bought. This means that the limited competitive pressure on sellers in our OO Market is primarily due to the imperfect information that restricts the products comparability.

Table 2: Buyers' responses to a product's own and the competing products' characteristics

Dependent Variable	Units sold	Units sold
Base price	-0.18*** (0.01)	-0.16*** (0.01)
Aggregate feature value	0.07*** (0.01)	0.06*** (0.01)
Aggregate feature price	-0.06** (0.01)	-0.04** (0.01)
Best competitor's base price	0.12*** (0.01)	-
Best competitor's aggregate feature value	-0.08*** (0.01)	-
Best competitor's aggregate feature price	0.07*** (0.01)	-
Best base price among competitors	-	0.10*** (0.02)
Best aggregate feature value among competitors	-	-0.01 (0.01)
Best aggregate feature price among competitors	-	-0.01 (0.01)
Number of features	-0.05 (0.07)	-0.10 (0.08)
Average number of features among competitors	-0.12 (0.09)	-0.25** (0.09)
Period	-0.03** (0.01)	-0.04** (0.01)
Constant	3.70*** (0.33)	3.73*** (0.78)
No. of observations	1320	1320
R-square	0.23	0.21

*Notes*: Standard errors are clustered on the market level. \*\*\* indicates significance at the 0.01 level, \*\* at the 0.05 level, and \* at the 0.10 level.

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<sup>&</sup>lt;sup>28</sup> This result indicates the importance of learning opportunities provided in markets. If inexperienced buyers' beliefs about the total price of products is elicited only once the buyers often underestimate this price (Morwitz, Greeenleaf and Johnson, 1998; Kim, 2006; Xia and Monroe, 2004) which is consistent with what we find during the initial periods. However, in the long run buyers on average acquire roughly correct beliefs about the overall net values of the product they buy in our experiment.

### 3.5 Buyers' overall welfare cost of obfuscation

We conclude our analysis of the market with obfuscation opportunities with a calculation of the overall welfare losses the buyers experience relative to a situation in which they appropriate the whole surplus in the market at zero search costs and zero mistakes – a situation that the NO Market closely approximates. We consider the following categories of buyer welfare losses in this exercise:

- (i) Losses due to a transfer of buyer surplus to the sellers via high prices even for the best available product in the market (as illustrated in Figure 4).
- (ii) Losses due to mistakes in failing to buy the best available product (again illustrated in Figure 4).
- (iii) Time wasted in searching an obfuscated market (as shown in Figure 11a).
- (iv) Losses due to failures to trade (Figure 12b).
- (v) Losses due to the fact that sellers failed to implement the surplus-maximizing level of add-on features (illustrated in Figure 4).

We make this welfare calculation for the entire 20 periods and again for the final 5 periods (16-20) because it is interesting to know how large the welfare losses are overall and also when the market has settled to a fairly stable situation as in periods 16-20. Our calculations indicate the following:

- **Result 8:** (a) Across all the periods, buyer welfare is 72% lower compared to a no-obfuscation benchmark setting in which sellers provide the surplus-maximizing add-on levels and buyers appropriate the whole surplus at no search cost. Sellers appropriate 63% of this overall loss for buyers via high prices (46%) and buyers' mistakes by failing to buy the best product (17%). 37% of the overall buyer welfare loss is due to time wasted searching in the market (13.5%), a failure to trade (15.5%), and sellers' inefficient choice of add-on levels (8%).
  - **(b)** In periods 16-20, buyer welfare is 44.2% lower compared to a no-obfuscation benchmark setting in which sellers provide the surplus-maximizing add-on levels and buyers appropriate the whole surplus at no search cost. Sellers appropriate 69% of this overall loss via high prices (42%) and buyer mistakes by failing to buy the best product (27%). 31% of the overall buyer welfare loss is due to time wasted searching in the market (18%), a failure to trade (9%), and sellers' inefficient choice of add-on levels (4%).

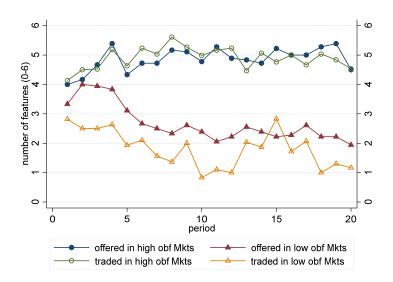
### 3.6 Surplus-Neutral Treatment

In the Surplus-Neutral Treatment (SNT), the experiment approximates a situation typically modelled in the theoretical literature on obfuscation. In this case, obfuscation via add-on features only increases complexity but does not come with enhanced surplus. While the data of our treatments with surplus-enhancing extra features support many qualitative predictions of these theories, we now examine whether our key results on obfuscation remain robust when product complexity does not add surplus. We summarize our main findings in the following.

**Result 9:** Obfuscation levels are significantly lower with surplus-neutral extra features compared to markets with surplus-enhancing extra features, and obfuscation is more fragile in the sense that some markets in the Surplus-Neutral Treatment converge towards low obfuscation levels and remove obfuscation almost completely. In these low obfuscation markets, buyers display an aversion against buying complex products, which appears to induce sellers to offer products with less complexity. In addition, buyers in these markets eventually appropriate almost the whole surplus.

Support for this result comes from Figure 13 below displaying the obfuscation levels and the fact that we observe a bi-modal obfuscation pattern across the 6 SNT markets: in 3 of the 6 markets (henceforth labelled "high obfuscation markets"), the average number of extra features across the entire 20 periods is 5.21, 4.63, and 4.73, respectively, while the average obfuscation levels in the other 3 markets (henceforth labelled "low obfuscation markets"), are only 3.18, 2.79, and 2.05, respectively. Moreover, the obfuscation level in the high obfuscation markets increases slightly over time (see Figure 13), while it declines in the low obfuscation market, although the initial obfuscation levels in the first three periods do not differ significantly in the two types of markets (p = 0.114). Consequently, the average number of extra features in offered and traded products is higher in the high obfuscation compared to the low obfuscation markets (p = 0.001 for offered products, p = 0.000 for traded products). Due to the existence of the low obfuscation markets in the Surplus-Neutral treatment, the overall average number of features in offered and traded products in the SNT is lower than in the treatments with surplus-enhancing extra features (p = 0.020 for offered and p = 0.025 for traded products).

Figure 13: Obfuscation levels in the market with obfuscation opportunities (OO Markets) in Surplus-Neutral Treatment (SNT)



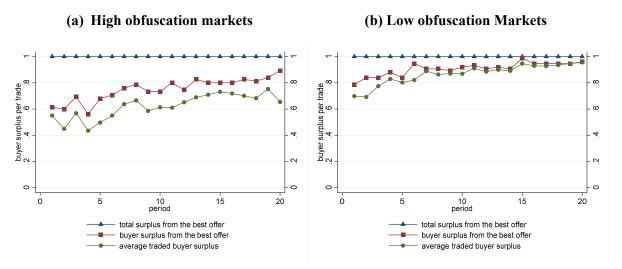
*Notes:* The figure shows the average number of features in both the offered and traded products in the OO markets of the Surplus-Neutral Treatment. The average number of extra features in offered and traded products is higher in the high obfuscation compared to the low obfuscation markets (p = 0.001 for offered products, p = 0.000 for traded products).

In high obfuscation markets, the average obfuscation level is very similar to that in the treatments with surplus-enhancing extra features (p = 0.304). Figure 13 also shows that the obfuscation levels in offered products and actually traded products are quite similar in high obfuscation markets of the SNT, a pattern

that is also present in HCT and CCT. In contrast, buyers on average buy products in the low obfuscation markets that are considerably less complex than the average offered product, a discrepancy that persists across the 20 periods (see Figure 13). In the long run (periods 16-20), the average complexity of offered products converges to only 2.3 extra features and the buyers buy products with only 1.4 extra feature in the low obfuscation markets.

As sellers are not able to sustain high levels of obfuscation in the low obfuscation markets, one would expect that the market would become relatively transparent over time and increasingly resemble a market without obfuscation – a conjecture that the data confirm quite nicely. Figure 14b below indicates that the buyer surplus converges to a very high level of 94% of maximal total surplus during periods 16-20 in low obfuscation markets. In contrast, Figure 14a shows that sellers in high obfuscation markets appropriate average profits of 30% of the maximal total surplus even in the long run (Period 16-20), which is only slightly lower than the sellers' surplus share of 32% in the treatments with surplusenhancing extra features. Figure 14a shows that there is a persistent gap in the buyers' surplus between the average traded and the best available product in the high obfuscation markets – a gap that is also significant during periods 16-20 (average gap is 13.2% with p = 0.042). In contrast, Figure 14b indicates that this gap completely vanishes over time in the low obfuscation markets, i.e. buyers in this market are able to identify and buy the best available product.

Figure 14: Buyer surplus in markets with obfuscation opportunities (OO Markets) in the Surplus-Neutral Treatment



*Notes:* These figures shows the buyer surplus in traded products, the buyer surplus associated with the best available offer in the market, and the total surplus associated with the best offer in the OO market. The figures are based on the data from the Surplus-Neutral Treatment. In this treatment, the total surplus from any (i.e., also the best) offer in the market is always 100% by construction because the number of chosen extra features has no surplus consequences.

Why are sellers unable to sustain a high level of obfuscation in the low obfuscation markets? Figure 13 shows that they initially tried to increase obfuscation as in the high obfuscation markets. And the fact that sellers in the high obfuscation markets of the SNT enforce higher obfuscation levels during the initial periods also suggests that a lack of obfuscation intentions on the sellers' side is unlikely to be responsible for the low obfuscation levels in Figure 13b. This figure already hints at a potential explanation by showing that buyers in the low obfuscation markets tend to buy products with lower complexity than those offered, a pattern that is absent in all other OO markets. To explore more carefully

why buyers behave this way, we examine the determinants of buying behavior econometrically analogously to Table 2. To find out whether buyers in the low obfuscation markets behave differently than buyers in the high obfuscation markets, we interact the determinants of buying behavior studied in Table 2 with a dummy variable that takes on the value of 1 if the observation comes from the low obfuscation markets. Our results are displayed in Table 3.

Table 3 replicates important insights we already observed in Table 2 (which reports the same regressions with the pooled data from HCT and CCT). In particular, the products' own base price, the base price of the best competing product, and the best base price among competitors are three highly influential and significant determinants of sellers' sales in both the high and the low obfuscation markets of the SNT. However, the table also highlights key differences between the high obfuscation and the low obfuscation markets. Most importantly, while the coefficient on the product's "number of features" is insignificant (and even positive) in the high obfuscation markets, the number of features has a large negative effect on a product's sales in the low obfuscation markets. Controlling for all other characteristics of a product (such as base price, aggregate feature price, aggregate feature value) and for the characteristics of the best competitor's products, the addition of two more extra features to a product reduces the number of sold units by 1.2 on average. We interpret this fact as an indication of buyers' aversion against complex products because it shows up, even though we control for all other characteristics of a product and the characteristics of the best competing product. Moreover, if it is indeed the case that buyers' in the low obfuscation market dislike complex goods, then we should also observe that the average number of features among the competitors raises the sales of a seller's own product, which is exactly what we observe: the coefficient on the interaction term between the average number of features in competitors' products and the "low obfuscation market" dummy is positive, large, and significant. Finally, complexity aversion already seems to be present in the low obfuscation markets from the very beginning because Figure 13 indicates that the complexity of the traded products is already lower than the complexity of the average product in the market during the first few periods.

One further noteworthy aspect in Table 3 is the following: Recall that in the markets with surplus-enhancing extra features (i.e., in the HCT and the CCT), a rise (decline) in the products own aggregate feature value (aggregate feature price) by 10 increases a product's sales by 0.7 (0.6) units. The corresponding increase in the product's sales is very similar at 0.5 (0.7) units in the high obfuscation markets.<sup>29</sup> This confirms that the elasticity of sales with regard to add-on characteristics is relatively low in markets with high obfuscation levels (like the HCT, the CCT and the high obfuscation markets of the SNT). In contrast, the market quickly becomes much more transparent in the low obfuscation markets of the SNT because of the lower obfuscation level, and this higher transparency may render a product's sales more elastic to the product characteristics. The remarkably large interaction terms between the "low obfuscation dummy" and the products aggregate feature values or aggregate feature prices is in line with this conjecture.

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<sup>&</sup>lt;sup>29</sup> These coefficients are not significant in the high obfuscation market of the SNT, but this is likely to be due to the fact that we only have three of these markets and we cluster standard errors on the market level, while we have six markets in both the HCT and the CCT.

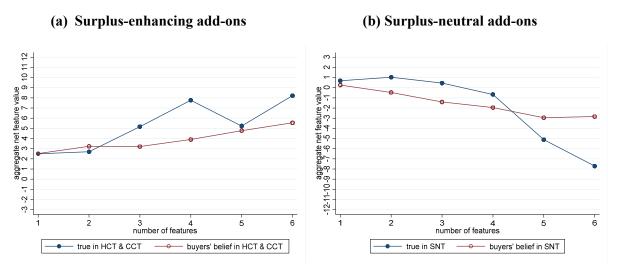
Table 3: Buyers' responses to a product's own and the competing products' characteristics in SNT

Dependent Variable   Units sold   Units sold			
Base price × low obf mkts  -0.14** (0.05)  Aggregate feature value  0.05  Aggregate feature value × low obf mkts  0.16* (0.07)  Aggregate feature price  -0.07  -0.07  (0.04)  Aggregate feature price × low obf mkts  0.16* (0.07)  -0.07  -0.07  -0.07  -0.07  -0.05  Best competitor's base price × low obf mkts  -0.11** -0.03  Best competitor's aggregate feature value -0.07  -0.07  -0.03  Best competitor's aggregate feature value -0.07  -0.08  -0.09  -0.09  -0.09  -0.00	Dependent Variable	Units sold	Units sold
Aggregate feature value	Base price		
Aggregate feature value × low obf mkts  0.16*	Base price $\times$ low obf mkts		
Aggregate feature price	Aggregate feature value		
Aggregate feature price × low obf mkts  -0.10* (0.05)  Best competitor's base price  0.11** (0.03)  Best competitor's base price × low obf mkts  -0.03  Best competitor's aggregate feature value  -0.07* (0.04)  Best competitor's aggregate feature value × low obf mkts  -0.08  Best competitor's aggregate feature value × low obf mkts  -0.07  Best competitor's aggregate feature price 0.08  -0.08  -0.06  -0.06  -0.06  -0.07  Best competitor's aggregate feature price 0.08  -0.008  Best competitor's aggregate feature price 0.08  -0.008  Best competitor's aggregate feature price 0.008  Best aggregate among competitors 0.009  Best base price among competitors -0.07** ∨ low obf mkts 0.02  Best aggregate feature value among competitors -0.02  Best aggregate feature value among competitors -0.05* × low obf mkts 0.002  Best aggregate feature value among competitors -0.05* × low obf mkts 0.002  Best aggregate feature price among competitors -0.00 0.002  Best aggregate feature price among competitors -0.03  √ low obf mkts 0.02  Number of features -0.13 0.11 0.15  Number of features × low obf mkts -0.58** -0.61** √ low obf mkts -0.15 -0.19 0.13 0.15  Average number of features among competitors × low obf mkts √ √  Constant and Constant × low obf mkts √ √  No. of observations -20  720	Aggregate feature value × low obf mkts		
Best competitor's base price   0.11** (0.03)	Aggregate feature price		
Best competitor's base price × low obf mkts	Aggregate feature price × low obf mkts		
Best competitor's base price $\times$ low obf mkts $\begin{pmatrix} -0.03 \\ (0.06) \end{pmatrix}$ = Best competitor's aggregate feature value $\begin{pmatrix} -0.07* \\ (0.04) \end{pmatrix}$ = $\begin{pmatrix} -0.004 \\ (0.04) \end{pmatrix}$ = Best competitor's aggregate feature value $\times$ low obf mkts $\begin{pmatrix} 0.07 \\ (0.04) \end{pmatrix}$ = Best competitor's aggregate feature price $\begin{pmatrix} 0.08 \\ (0.04) \end{pmatrix}$ = $\begin{pmatrix} -0.06 \\ (0.04) \end{pmatrix}$ = Best competitor's aggregate feature price $\times$ low obf mkts $\begin{pmatrix} 0.08 \\ (0.08) \end{pmatrix}$ = $\begin{pmatrix} 0.09*** \\ (0.02) \end{pmatrix}$ = Best base price among competitors $\begin{pmatrix} -0.09*** \\ (0.02) \end{pmatrix}$ = Best base price among competitors $\begin{pmatrix} -0.07** \\ (0.02) \end{pmatrix}$ = Best aggregate feature value among competitors $\begin{pmatrix} -0.07** \\ (0.02) \end{pmatrix}$ = Best aggregate feature value among competitors $\begin{pmatrix} -0.02 \\ (0.02) \end{pmatrix}$ = Best aggregate feature value among competitors $\begin{pmatrix} -0.05* \\ (0.02) \end{pmatrix}$ = Best aggregate feature price among competitors $\begin{pmatrix} -0.05* \\ (0.02) \end{pmatrix}$ = $\begin{pmatrix} -0.05* \\ (0.02) \end{pmatrix}$ = Best aggregate feature price among competitors $\begin{pmatrix} -0.00 \\ (0.00) \end{pmatrix}$ = $\begin{pmatrix} -0.03 \\ (0.02) \end{pmatrix}$ = $\begin{pmatrix} 0.013 \\ (0.14) \end{pmatrix}$ = $\begin{pmatrix} 0.13 \\ (0.14) \end{pmatrix}$ = $\begin{pmatrix} 0.13 \\ (0.14) \end{pmatrix}$ = $\begin{pmatrix} 0.15 \\ (0.21) \end{pmatrix}$ = $\begin{pmatrix} 0.02 \\ (0.20) \end{pmatrix}$ = Average number of features among competitors $\begin{pmatrix} 0.13 \\ (0.14) \end{pmatrix}$ = $\begin{pmatrix} 0.15 \\ (0.13) \end{pmatrix}$ = $\begin{pmatrix} 0.15 \\ (0.13) \end{pmatrix}$ = $\begin{pmatrix} 0.15 \\ (0.13) \end{pmatrix}$ = $\begin{pmatrix} 0.15 \\ (0.12) \end{pmatrix}$ = $\begin{pmatrix} 0.08 \\ (0.15) \end{pmatrix}$ = $\begin{pmatrix} 0.08 \\ (0$	Best competitor's base price		-
Best competitor's aggregate feature value $\begin{pmatrix} -0.07* \\ (0.04) \end{pmatrix}$ = $\begin{pmatrix} 0.04 \\ (0.04) \end{pmatrix}$ = $\begin{pmatrix} 0.04 \\ \times \log \log$	Best competitor's base price × low obf mkts		-
Best competitor's aggregate feature value $\times$ low obf mkts $\times$ (0.07) $\times$ Best competitor's aggregate feature price $\times$ (0.04) $\times$ Best competitor's aggregate feature price $\times$ (0.04) $\times$ Best competitor's aggregate feature price $\times$ (0.08) $\times$ low obf mkts (0.08) $\times$ Best base price among competitors $\times$ (0.02) Best base price among competitors $\times$ low obf mkts (0.02) Best aggregate feature value among competitors $\times$ (0.02) Best aggregate feature value among competitors $\times$ (0.02) Best aggregate feature value among competitors $\times$ (0.02) Best aggregate feature price among competitors $\times$ (0.02) Best aggregate feature price among competitors $\times$ (0.00) Best aggregate feature price among competitors $\times$ (0.00) Best aggregate feature price among competitors $\times$ (0.02) Number of features $\times$ (0.13) (0.14) (0.15) Number of features $\times$ low obf mkts (0.21) (0.20) Average number of features among competitors (0.15) (0.13) (0.15) Average number of features among competitors (0.16) (0.22) Period and Period $\times$ low obf mkts $\times$ (0.16) (0.22) Period and Period $\times$ low obf mkts $\times$ (0.16) (0.22) Period and Constant $\times$ low obf mkts $\times$ (0.16) (0.22)	Best competitor's aggregate feature value	-0.07*	-
Best competitor's aggregate feature price $\times$ low obf mkts (0.08)  Best base price among competitors - 0.09*** (0.02)  Best base price among competitors 0.07** (0.02)  Best aggregate feature value among competitors 0.02 (0.02)  Best aggregate feature value among competitors 0.05* (0.02)  Best aggregate feature value among competitors 0.05* (0.02)  Best aggregate feature price among competitors 0.00 (0.00)  Best aggregate feature price among competitors 0.00 (0.00)  Best aggregate feature price among competitors 0.03 (0.02)  Number of features 0.03 (0.02)  Number of features × low obf mkts - 0.58** - 0.61** (0.21) (0.20)  Average number of features among competitors - 0.15 (0.13) (0.15)  Average number of features among competitors - 0.15 (0.13) (0.15)  Average number of features among competitors - 0.15 (0.13) (0.15)  Average number of features among competitors - 0.15 (0.13) (0.15)  Average number of features among competitors - 0.46** (0.68** v. low obf mkts) - 0.68** v. low obf mkts - 0.61** (0.16) (0.22)  Period and Period × low obf mkts - $\sqrt{}$ $\sqrt{}$ $\sqrt{}$ V. Constant and Constant × low obf mkts - $\sqrt{}$ $\sqrt{}$ V. No. of observations - 720 720		0.04	-
$ \begin{array}{c} \times \   \text{low obf mkts} & (0.08) \\ \\ \text{Best base price among competitors} & - & 0.09^{***} \\ (0.02) \\ \\ \text{Best base price among competitors} & - & -0.07^{**} \\ \times \   \text{low obf mkts} & (0.02) \\ \\ \text{Best aggregate feature value among competitors} & - & 0.02 \\ (0.02) \\ \\ \text{Best aggregate feature value among competitors} & - & -0.05^* \\ \times \   \text{low obf mkts} & (0.02) \\ \\ \text{Best aggregate feature price among competitors} & - & 0.00 \\ (0.00) \\ \\ \text{Best aggregate feature price among competitors} & - & -0.03 \\ \times \   \text{low obf mkts} & (0.02) \\ \\ \text{Number of features} & 0.13 \\ (0.14) & (0.15) \\ \\ \text{Number of features} \times \   \text{low obf mkts} & -0.58^{**} \\ (0.21) & (0.20) \\ \\ \text{Average number of features among competitors} & -0.15 \\ \times \   \text{low obf mkts} & (0.15) \\ \\ \text{Average number of features among competitors} & 0.46^{**} \\ \times \   \text{low obf mkts} & (0.16) \\ \\ \text{Constant and Constant} \times \   \text{low obf mkts} &  &  \\ \\ \text{Constant and Constant} \times \   \text{low obf mkts} &  &  \\ \\ \text{No. of observations} & 720 & 720 \\ \\ \end{array}$	Best competitor's aggregate feature price		-
Best base price among competitors $\times$ low obf mkts $= -0.07^{**}$ (0.02)  Best aggregate feature value among competitors $= -0.02$ (0.02)  Best aggregate feature value among competitors $= -0.05^{**}$ (0.02)  Best aggregate feature price among competitors $= -0.05^{**}$ (0.02)  Best aggregate feature price among competitors $= -0.00$ (0.00)  Best aggregate feature price among competitors $= -0.03$ (0.02)  Number of features $= -0.03$ (0.02)  Number of features $= -0.13$ (0.14) (0.15)  Number of features $\times$ low obf mkts $= -0.58^{**}$ (0.21) (0.20)  Average number of features among competitors $= -0.15$ (0.13) (0.15)  Average number of features among competitors $= -0.15$ (0.13) (0.15)  Average number of features among competitors $= -0.15$ (0.13) (0.15)  Average number of features among competitors $= -0.15$ (0.13) (0.15)  Average number of features among competitors $= -0.15$ (0.16) (0.22)  Period and Period $\times$ low obf mkts $= -0.61$ (0.16) (0.22)  Constant and Constant $\times$ low obf mkts $= -0.50$ (0.16) (0.22)			-
$ \begin{array}{c} \times \text{ low obf mkts} & (0.02) \\ \\ \text{Best aggregate feature value among competitors} & - & 0.02 \\ (0.02) \\ \\ \text{Best aggregate feature value among competitors} & - & -0.05* \\ \times \text{ low obf mkts} & (0.02) \\ \\ \text{Best aggregate feature price among competitors} & - & 0.00 \\ (0.00) \\ \\ \text{Best aggregate feature price among competitors} & - & -0.03 \\ \times \text{ low obf mkts} & (0.02) \\ \\ \text{Number of features} & 0.13 & 0.11 \\ (0.14) & (0.15) \\ \\ \text{Number of features} \times \text{ low obf mkts} & -0.58** & -0.61** \\ (0.21) & (0.20) \\ \\ \text{Average number of features among competitors} & -0.15 & -0.19 \\ (0.13) & (0.15) \\ \\ \text{Average number of features among competitors} & 0.46** & 0.68** \\ \times \text{ low obf mkts} & (0.16) & (0.22) \\ \\ \text{Period and Period} \times \text{ low obf mkts} & \sqrt{} & \sqrt{} \\ \\ \text{Constant and Constant} \times \text{ low obf mkts} & \sqrt{} & \sqrt{} \\ \\ \text{No. of observations} & 720 & 720 \\ \hline \end{array} $	Best base price among competitors	-	
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$ \times \text{ low obf mkts} \qquad \qquad (0.02) $ Number of features $ \begin{array}{c} 0.13 & 0.11 \\ (0.14) & (0.15) \\ \end{array} $ Number of features × low obf mkts $ \begin{array}{c} -0.58** & -0.61** \\ (0.21) & (0.20) \\ \end{array} $ Average number of features among competitors $ \begin{array}{c} -0.15 & -0.19 \\ (0.13) & (0.15) \\ \end{array} $ Average number of features among competitors $ \times \text{ low obf mkts} \qquad 0.68** \\ \times \text{ low obf mkts} \qquad 0.68** \\ \times \text{ low obf mkts} \qquad  \qquad  \\ \end{array} $ Constant and Constant × low obf mkts $ \begin{array}{c}  &  \\ \end{array} $ No. of observations $ \begin{array}{c} 720 & 720 \\ \end{array} $	Best aggregate feature price among competitors	-	
Number of features × low obf mkts $ \begin{array}{c} (0.14) & (0.15) \\ -0.58^{**} & -0.61^{**} \\ (0.21) & (0.20) \\ \end{array} $ Average number of features among competitors $ \begin{array}{c} -0.15 & -0.19 \\ (0.13) & (0.15) \\ \end{array} $ Average number of features among competitors $ \begin{array}{c} 0.46^{**} & 0.68^{**} \\ \times \text{ low obf mkts} & (0.16) & (0.22) \\ \end{array} $ Period and Period × low obf mkts $ \begin{array}{c} \sqrt{} & \sqrt{} \\ \hline \end{array} $ Constant and Constant × low obf mkts $ \begin{array}{c} \sqrt{} & \sqrt{} \\ \hline \end{array} $ No. of observations $ \begin{array}{c} 720 & 720 \\ \hline \end{array} $		-	
Average number of features among competitors	Number of features	****	
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$\times$ low obf mkts     (0.16)     (0.22)       Period and Period $\times$ low obf mkts $\sqrt{}$ $\sqrt{}$ Constant and Constant $\times$ low obf mkts $\sqrt{}$ $\sqrt{}$ No. of observations     720     720	Average number of features among competitors		
Constant and Constant × low obf mkts $\sqrt{}$ No. of observations 720 720			
No. of observations 720 720	Period and Period × low obf mkts	$\checkmark$	$\sqrt{}$
	Constant and Constant × low obf mkts	$\checkmark$	$\checkmark$
R-square 0.29 0.30	No. of observations	720	720
<u> </u>	R-square	0.29	0.30

Notes: The standard errors in the regressions are clustered on the market level. \*\*\* indicates significance at the 0.01 level, \*\* at the 0.05 level, and \* at the 0.10 level.

The previous analyses suggest that buyers' complexity aversion is likely to be a reason for the fragility of obfuscation in the Surplus-Neutral Treatment (SNT). But why are buyers averse to complex products in the SNT, but not in the treatments with surplus-enhancing add-ons? Figure 15 below provides a potential answer to this question. Buyers in the treatments with surplus-enhancing add-ons experience and believe that there is a positive relationship between the products' aggregate net feature values and the number of add-ons (Figure 15a). In contrast, buyers in the SNT experience and believe on average that this relationship is negative (Figure 15b). Thus, a higher number of add-ons is associated and believed to be associated with better products in the treatments with surplus-enhancing add-ons, while the opposite is the case in the Surplus-Neutral Treatments. In other words, the buyers had no reason to be suspicious of or averse to products with many add-ons in the markets with surplus-enhancing add-ons but they had good reason to be averse to complex products in the SNTs. We believe that this explains why complexity aversion, and the associated fragility of obfuscation, shows up only in markets with surplus-neutral add-ons.

Figure 15: The relationship between products' aggregate net feature values and the number of add-ons in the OO Markets with surplus-enhancing and with surplus-neutral add-ons.



*Notes:* The figures show the buyers' beliefs about the relationship between products' aggregate net feature values and the number of features and the actual relationship. Figure (a) illustrates the actual and believed relationship in the treatments with surplus-enhancing add-ons (HCT and CCT) while Figure (b) shows the corresponding believed and actual relationships in the treatment with surplus-neutral add-ons (SNT).

## 4 Summary and Conclusions

While traditional economic models of competitive markets assumed that consumers are able to understand and compare all the products in the market, consumers' attention and information is costly and their cognitive capacities are limited. These constraints appear particularly important in modern economies characterized by a flood of differentiated products with an overwhelming number of add-on features. Electronic commerce may, in principle, facilitate product comparisons and thus foster competition, but firms may deliberately weaken competition by obfuscating their products, i.e., by making their products complex and thus increasing consumers' search effort.

To understand the consequences of obfuscation via add-ons on market prices, competition, and consumer welfare, we designed an experiment with obfuscation opportunities for the sellers and endogenous search opportunities for buyers. To identify the causal impact of obfuscation opportunities, we contrast this market with obfuscation opportunities with a control market in which a policy intervention ensures that all the products are represented by just one quality-adjusted price. We find that while price levels converge very quickly to marginal cost in the markets with no obfuscation, obfuscation opportunities enable sellers to appropriate about 32% of the total surplus that buyers would have received if the prices were at the marginal costs. Sellers can appropriate this share of the total market surplus even in the long run, i.e., even during the final periods of our market experiment.

This decrease in buyer welfare results from sellers' active use of obfuscation opportunities and, if given the chance, they even obfuscate to the point where additional add-ons are surplus-reducing. Buyers, as a consequence, have to waste valuable time to search in the market to obtain information about the products' add-on features. Yet, their search on average only covers less than half of the products in the market, and they fail to see roughly half of the extra features of the products that they visit. Because of this limited information acquisition, competitive forces are significantly mitigated in the market. Buyers are attracted by the transparent part of products but are significantly less sensitive to the "hidden" extra features of products. These behavioral tendencies of buyers generate specific obfuscation incentives for the sellers: their headline prices drop quickly to very low levels, sometimes even below marginal cost, while the extra features generate stable and sizable profits. The best available products in these markets have a limited competitive impact and enable sellers of worse products to still sell them at a profit. This reduction in buyer welfare in markets with obfuscation opportunities is in sharp contrast to the control market with full transparency, where the best available product is transparent, allowing buyers to appropriate the whole surplus in the market. Therefore, obfuscation by add-on features is a very powerful tool for sellers to escape the "zero-profit" trap in markets that would otherwise be very competitive.

However, we also find that obfuscation is considerably more fragile when add-ons are on average not surplus-enhancing and thus obfuscation is purely exploitative. We find, in particular, that buyers are reluctant to buy more complex products in some of the markets with surplus-neutral add-ons, and this reluctance prevails even if we control for all other aspects of the good. In these markets, obfuscation therefore unravels over time and the market approaches competitive conditions. A plausible reason for buyers' reluctance to buy complex products is that higher product complexity is associated with less valuable goods for the buyers in these markets – a fact the buyers realize. On the other hand, obfuscation levels are very stable when add-on features are surplus-enhancing. A potential reason for this is that when add-ons generate extra surplus on average, sellers only need to price the add-ons above cost rather than above buyers' valuations to earn profits. In this case, higher product complexity is associated with more valuable goods for the buyers – which is indeed the case in the OO markets with surplus-enhancing add-ons. We show that buyers perceive this fact and, therefore, they may feel compensated to some extent for the search activities complexity generates. In contrast, buyers on average derive no benefit whatsoever from their search activities if the add-ons are not surplus enhancing and if sellers try to exploit buyers by charging prices for the add-ons that are above the add-ons' cost. Under these conditions, it is thus more likely that buyers' complexity aversion will hurt sellers with complex products, therefore reducing individual sellers' incentive to obfuscate. We believe that these findings provide a deeper understanding of the forces that sustain obfuscation in markets and may inform theory construction in this important area of research.

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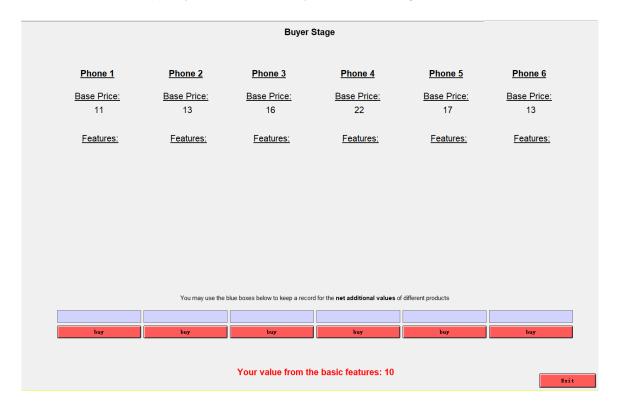
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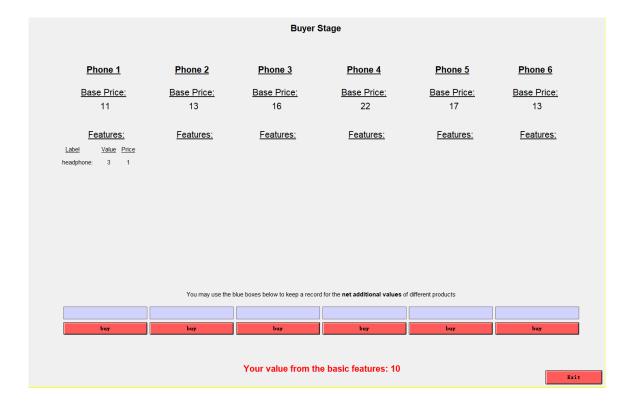
# **Appendix**

Figure A1: example screens in the buyer stage in market with obfuscation opportunity

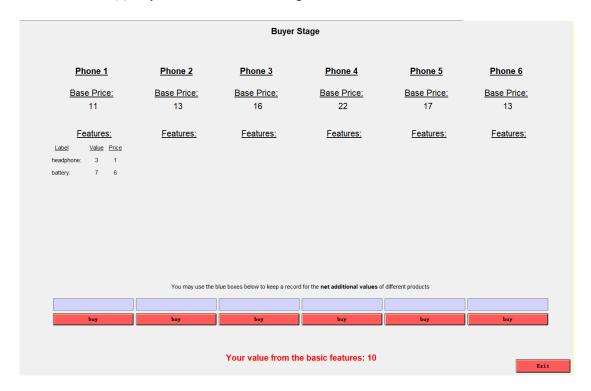
(a) Buyer screen before buyer searched though add-ons



(b) Buyer Screen after searching the first add-on of Phone 1



#### (c) Buyer Screen after searching the second add-on of Phone 1



*Notes:* In the buyer stage, buyers first immediately only see (a). With each click on, e.g., Phone 1, buyers can see one more feature of that product like in (b) and (c). If buyers click on another product, then the features of this other product are also shown one by one as buyers click.

Figure A2: example screens of the feedback stage

## (a) Feedback screen for seller of phone 5

Feedback Stage																	
Phone 1 Phone		none 2	2	Phone 3			Phone 4			Phone 5				Phone 6			
Base Price:		Base Price: 13		Base Price: 16		Base Price: 22			Base Price: 17			Base Price: 13					
<u>Features:</u>			Features:			<u>Features:</u>		<u>Features:</u>			Features:			<u>Features:</u>			
Label	Value	Price	Label	Value		Label	Value	Price	Label	Value Price		_	Value	Price	Label	Value	
headphone:	3	1	weight:	9	7	battery:	5	9	None		capa		2	3	capacity		3
battery:	7	6	shipping:	5	9	packaging:	8	3			weigl		7	2	battery:	4	7
warrranty:	6	3	warrranty:	8	3	headphone:	2	3			came		3	1			
capacity:	1	8				weight: camera:	7	2			displa	iy:	6	6			
Sum of feature prices: 18 Sum of feature values: 17 Sum of feature costs: 8.5 Earnings from extra features: 9.5 Total earnings from a trade: 15.5		Sum of featur Sum of featur Sum of featur Earnings for Total earnings	values: 2 costs: 11 extra feat	2 .0 ures: 8.0	Sum of feature Sum of feature Sum of feature Earnings for Total earnings	values: 2 costs: 12 extra fea	.5 :ures: 5.5	Earnings fro		Sum Sum 3.0 Earr 7.0 Tota Unit	of feature of feature ings from I earnings s sold: 2 I earnings	e values: e costs: 9 extra fea from a t	18 .0 itures: 3.0 rade: 15.0	Sun Sun D Earr D Tota		ues: 6	
																	OK

## (b) Feedback screen for a buyer

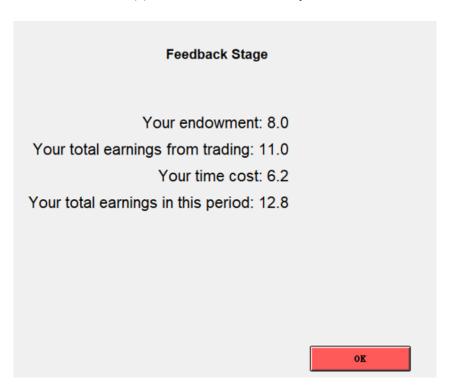
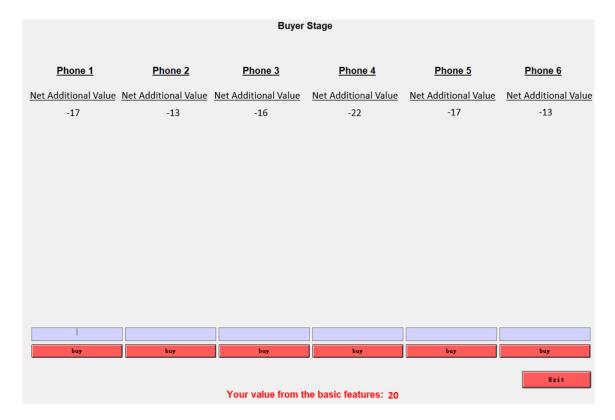


Figure A3: an example screen of the buyer stage in NO market



*Notes:* The overall net value  $v_o$  of products is described with the name "net additional value", so "net additional value" is shown on the buyer's stage in the NO market.