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ABSTRACT

To Buy or Not to Buy? Price Salience in an Online Shopping Field Experiment*

We examine whether shrouding or partitioning of a surcharge raises demand in online shopping. In a field experiment with more than 34,000 consumers, we find that consumers in the online shop of a cinema are more likely to select tickets for a 3D movie when the 3D surcharge is shrouded, but they also drop out more often when the overall price is shown at the checkout. In sum, the demand distribution is independent of the price presentation. This result outlines the limits of the effectiveness of shrouding practices.

JEL Classification: D81, C93

Keywords: salience, inattention, shrouding, price partitioning, field experiment

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1. Introduction

It is well-known that consumers have limited attention and therefore often act myopically rather than in a sophisticated way. In particular, the presentation and salience of prices can affect purchasing behavior and should be taken into consideration by policy-makers (see Bernheim and Taubinsky, 2018, or Gabaix, 2019). Yet, optimal policy design requires good knowledge of the circumstances under which inattention and price (non-)salience influence consumers.

Across many industries, firms attempt to increase demand by making surcharges non-salient. Often these non-salient surcharges correspond to a substantial share of the total price, and discovering the exact amount of the surcharge or canceling an initiated purchase is complicated through various frictions (e.g., a long and intransparent purchase process). Some budget airlines, for instance, offer flights for as little as 19.99 Euro, which does not include taxes of 30 Euro or credit-card fees of 20 Euro.[1] Typically, the additional fees can be discovered only toward the end of a rather long purchase process. Other examples include fees for shipping and handling, which can be substantial for cheap products (at least in relative terms), and which are sometimes hidden in the fine print until the purchase is confirmed, again making the price discovery quite costly.[2] Even without any frictions in the process of discovering the total price or canceling an initiated purchase process, non-salient surcharges can increase demand, at least when these surcharges are not very substantial.[3] But what are the boundaries of such salience effects?

We conducted a natural field experiment to answer the question whether the presentation of surcharges affects demand even if (i) the surcharge is relatively large, and (ii) there are no frictions in the process of discovering the total price and canceling an initiated purchase. More precisely, we ask whether shrouding or partitioning a substantial surcharge (of a little less than half the base price) just at the beginning of a purchase process increases demand. In contrast to previous studies, our experimental design reduces potential frictions in the purchase process by as much as possible, at the same time maintaining a sizeable and thus important surcharge.

[1] At least in the European Union, this practice of pricing flight tickets is no longer allowed: for travel tickets, the European Union Article 23 of Regulation (EC) No 1008/2008 requires that "the final price to be paid shall at all times be indicated and shall include the applicable air fare or air rate as well as all applicable taxes, and charges, surcharges and fees which are unavoidable and foreseeable at the time of publication."

[2] The surcharge for shipping and handling in the seminal studies by Hossain and Morgan (2006) and Brown et al. (2010) for goods (such as CDs) purchased via eBay auctions amounts to more than 30% of the opening bid/effective reserve price (i.e., a similar ratio of base price to surcharge as in our study), and these additional fees are transparently revealed to the consumer only after confirming the purchase.

[3] Examples include the laboratory experiments by Feldman and Ruffle (2015) and Feldman et al. (2018).

In cooperation with a large German cinema, we manipulated the presentation of prices for 3D movies in the cinema's online store. The price of a 3D movie ticket consists of a base price, which varies across movies and days, plus a fixed 3D surcharge of 3 Euro (i.e., around 40% of the base price for a regular movie show). Using a between-subjects design, we implemented three treatments: in *Inclusive*, the full price including the 3D surcharge is presented; in *Shrouded*, only the base price with a small footnote indicating the additional 3D surcharge is shown; and in *Partitioned*, the base price and the 3D surcharge are presented separately. In all three treatments, prior to confirming the purchase, consumers were presented the total price (including the surcharge) at the checkout. We can thus examine whether the presentation of the 3D surcharge has an impact on a consumer's likelihood of (1) proceeding to the checkout and (2) actually buying tickets. Examining both parts of the purchase process separately allows us to study whether consumers, who selected tickets only due to the manipulation of the price presentation, still buy tickets when the total price is transparently shown prior to the purchase.

Tracking more than 34,000 consumers over a period of nine months, we find that shrouding of the 3D surcharge significantly increases the likelihood of a consumer placing tickets for a 3D movie in her shopping basket. But we also find that shrouding of the surcharge does *not* affect actual purchases. This null-result arises from consumers in *Shrouded* dropping out much more likely once they learn the total price (including the surcharge) at the checkout. We conclude that in our setup – with a substantial surcharge and no frictions in the process of discovering the price and canceling an initiated purchase process – shrouding the surcharge has no effect on demand. Just partitioning the surcharge without shrouding it, in contrast, neither affects the likelihood of placing tickets in the shopping basket nor the likelihood of actually buying tickets.

This lack of demand effects in our experiment seemingly contrasts with previous findings in the literature. Even in settings where – just like in our experiment – the total price was presented prior to the purchase,[4] several studies have documented substantial demand effects of shrouding sales taxes (Chetty et al., 2009; Feldman and Ruffle, 2015; Feldman et al., 2018) or other sales surcharges (Blake et al., 2018).[5] These previous studies have in common, however, that taxes

[4] Other studies have documented shrouding effects in settings where consumers did not learn the total price before confirming the purchase (Morwitz et al., 1998; Hossain and Morgan, 2006; Brown et al., 2010; Finkelstein, 2009). Taubinsky and Rees-Jones (2018), for instance, find that shrouding sales taxes, when displaying prices, increases demand on average, and the more so the smaller the shrouded tax amount is (see also Morrison and Taubinsky, 2020).

[5] One exception is the tax-deduction treatment in Feldman and Ruffle (2015), where subjects are informed that taxes initially included in the price will be deducted at the checkout. Feldman and Ruffle (2015) find that purchases in this treatment do not differ from purchases in a treatment where the exact price to be paid is displayed right from the beginning. Hence, subjects in their experiment appear to internalize the non-salient tax deduction.

or surcharges are much smaller in relative terms (between 8% and 22% of the base price), and the process of learning the total price or canceling the purchase process involves some frictions. In Chetty et al.'s (2009) seminal field experiment at a supermarket, for instance, consumers learn tax-inclusive prices at the checkout, when typically being "observed" by other consumers waiting in line. Here, social image concerns ("Others might think I cannot afford the items in my basket") might prevent consumers from canceling a purchase. Moreover, since consumers often buy a basket of goods, it might be hard to associate an unexpected price hike with a specific product. Re-optimizing the shopping basket in response to learning tax-inclusive prices further requires time and effort. Feldman and Ruffle (2015) and Feldman et al. (2018) replicate such a shopping environment in the lab. Subjects buy a basket of household items, which can be re-optimized after learning tax-inclusive prices. As in Chetty et al. (2009), unexpected price hikes for the basket are not transparently attributed to specific products, making re-optimization costly. Blake et al. (2018) document demand effects of shrouding sales surcharges on tickets for shows and concerts. Due to the high consumption value (arguably, much higher than for watching a movie), their results might be driven by an *attachment effect*: a loss-averse consumer becomes attached to the idea of being at a show, which may hinder her from canceling the purchase.[6] In addition, the consequences of canceling a purchase process are much more severe in their setting compared to ours: when canceling the purchase of a concert ticket, a consumer risks not getting any tickets, in case she later changes her mind and the concert is already sold out. Our setup minimizes all these frictions: cancellations are unobserved by other consumers, ruling out social image concerns; the consumption value is low and the consequences of canceling a purchase process are mild, both of which limits the scope for the attachment effect; and the purchase process is very short and transparent, which limits re-optimization costs. The combination of a substantial surcharge and a frictionless purchase process can, thus, explain why – in contrast to existing studies – we do not find demand effects of shrouding surcharges.[7]

While we establish a bound on the effectiveness of salience manipulations, our experimental design does not allow us to pin down the exact mechanism driving our results. On the one hand, the surcharge in our experiment comprises a relatively large share of the base price. Hence, appropriately reacting to the surcharge (once it is revealed to the consumer) might be more important in our study than it was in previous ones. On the other hand, we also reduce potential

[6] Similarly, albeit attached to the idea of buying a product, a consumer might actively disregard non-salient information on surcharges that conflict with the intention to buy. Feldman and Ruffle (2015) denote this mechanism as the confirmation bias theory of salience.

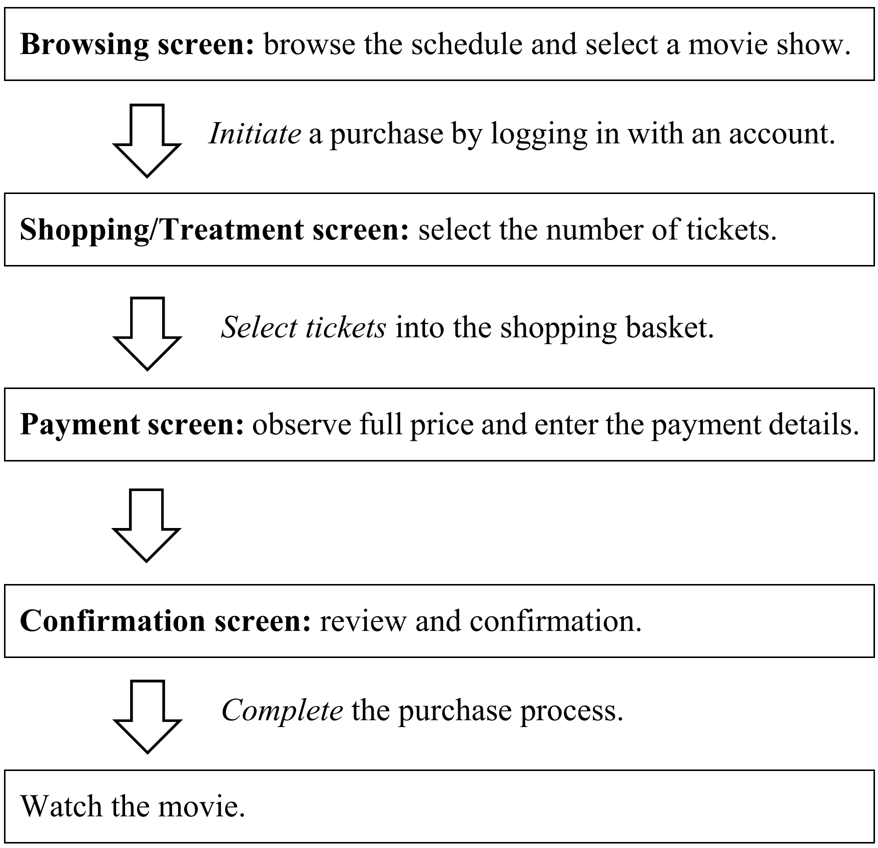
[7] Reassuringly, all existing studies that also record cancellations – after items have already been selected – find that a considerable share of consumers cancel the initiated purchase once the total price (including the surcharge) is presented (see the column "If full price is presented" in the overview table presented in Appendix A).

frictions in the purchase process to a minimum. In sum, we are not able to say whether the different results are due to the size of the surcharge, due to the frictionless environment, or due to a combination of the two. While we leave this question to future research, we still establish clear boundaries of salience effects that were underexplored so far.

2. Experimental Design

In a natural field experiment, we varied the presentation of prices for 3D movies in the online store of a large German multiplex cinema. The price of a ticket for a 3D movie always includes the base price for a movie ticket plus a 3D surcharge, which amounts – as it is typical for German cinemas – to 3 Euro. Each 3D movie is also shown in a 2D variant for which the surcharge does not apply. These 2D shows take place in a different hall within the same multiplex at a potentially different time.

Figure 1. *Purchase process in the online store.*



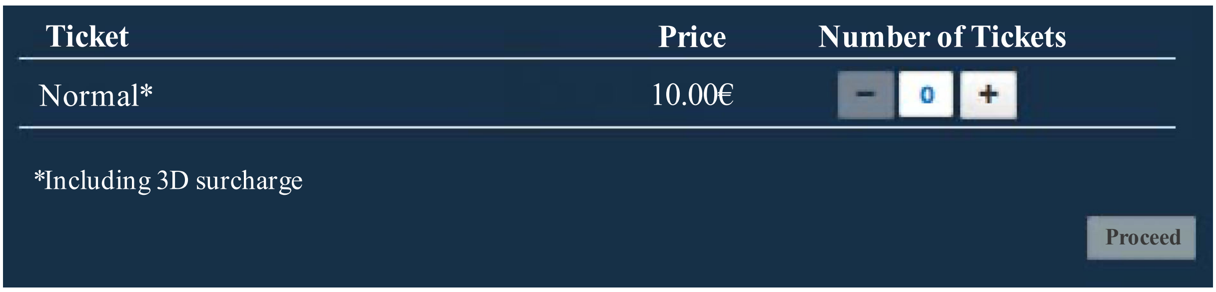
Purchase process. As illustrated in Figure 1, the purchase process in the cinema's online store consists of four distinct screens: First, the consumer browses the cinema schedule (see Figure D.1 in the Appendix for a screenshot). The schedule includes all shows running within the next seven days. After choosing a certain show, the consumer has to log in with an e-mail address and a password. We refer to this step as the consumer *initiating* a purchase process. On the *Shopping* screen, the consumer observes, depending on the treatment, either the full price (including the surcharge), or only the base price, or both price components separately (for details, see Figure 2 below). The consumer can then select the number of tickets that she would like to buy for this particular show. We say that the consumer *selects tickets* if she proceeds to the *Payment* screen, where in all treatments the total price is presented and the consumer has to enter her payment details. On the *Confirmation* screen, all relevant information is summarized and the consumer has finally to confirm the purchase. We say that the consumer *completes* the purchase if she confirms on this last screen.

The main feature of our experiment is that the treatment variation concerns only the *Shopping* screen on which we manipulate the presentation of prices. The cinema schedule (i.e., the *Browsing* screen) as well as the *Payment* and *Confirmation* screens are identical across all three treatments. Importantly, while browsing the cinema schedule, consumers do not observe any information on the base price or the 3D surcharge.

Treatments. To study the implications of price partitioning and shrouding for shopping behavior, we vary the presentation of prices on the *Shopping* screen across three treatments. Strictly speaking, the total price has to be partitioned in order for the 3D surcharge to be shrouded, so that shrouding is a special case of price partitioning. Whenever we speak of price partitioning throughout this study, we mean price partitioning without shrouding.

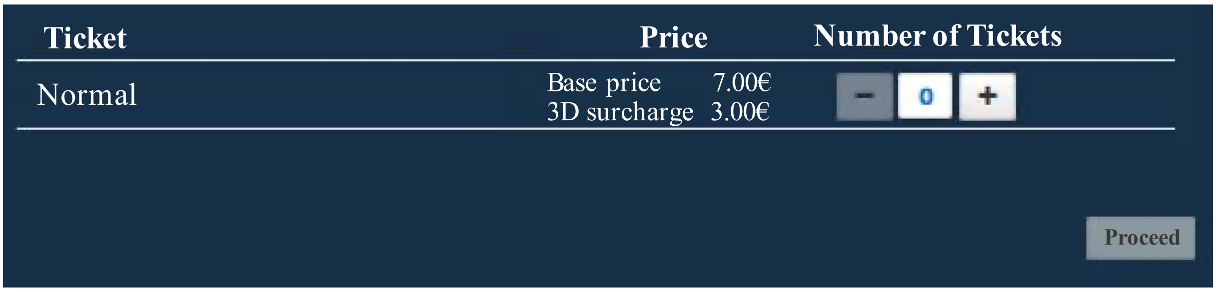
- **Inclusive**: In the first treatment, we present the overall ticket price, including the 3D surcharge, and add a footnote stating that the surcharge is already included (for an illustration, see Figure 2 (a), and for the actual screen, see Figure D.2 in the Appendix). This price presentation was also used before our intervention.

Figure 2 (a). *Stylized design of the Shopping screen in Inclusive.*



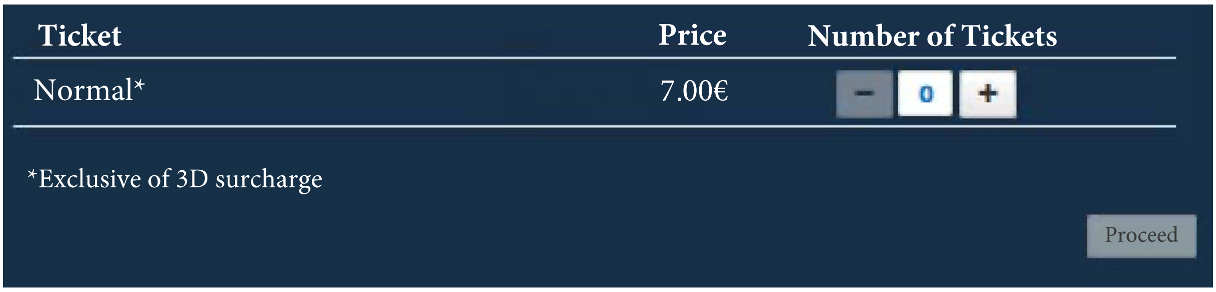
- **Partitioned**: In this treatment, we split up the full price by presenting the two price components – the base price and the 3D surcharge – in separate lines, but identical font and font size (see Figure 2 (b) and Figure D.3 in the Appendix).

Figure 2 (b). *Stylized design of the Shopping screen in Partitioned.*



- **Shrouded**: In the third treatment, we "shroud" the 3D surcharge by presenting the base price and mentioning the additional surcharge (but not the exact amount) only in a footnote (see Figure 2 (c) and Figure D.4 in the Appendix).[8]

Figure 2 (c). *Stylized design of the Shopping screen in Shrouded.*



Randomization and identifying assumption. In order to buy tickets for a certain movie via the cinema's online store, a consumer has to browse the cinema's schedule on the homepage, then she has to click on a particular show of this movie, and afterwards she has to log in with her email address and a password. Only after logging in does a consumer see the *Shopping*

[8] Since 3D surcharges are almost the same across cinemas all over Germany, the typical consumer is not only aware of the fact that such a surcharge applies, but can be assumed to have a good knowledge of its size, even before the first purchase in our cinema (and, for sure, after the first purchase). As Bernheim and Taubinsky (2018) argue, if consumers were used to see the price exclusive of the surcharge (e.g., consumers being used to tax-exclusive prices as in Chetty et al., 2009), good knowledge about the surcharge might be problematic, because consumers could misinterpret the surcharge-inclusive price as an increase in the base price. This should be of no concern in our setup, as surcharge-inclusive prices were used prior to our intervention.

screen of the purchase process (i.e., the price of a ticket as presented above) and choose how many tickets she would like to have. Each consumer has a unique user ID, based on which we randomized our treatment assignment. This implies that each consumer is assigned the same treatment over the entire duration of the experiment. Our identifying assumption, then, is that the random assignment of the treatment worked properly.

Hypotheses. Building on the literature on inattention and salience effects, we expect that the likelihood of selecting tickets for a 3D movie is lower in *Inclusive* than in *Partitioned*, and lower in *Partitioned* than in *Shrouded*. The former relies on the well-known contrast effect (e.g., Schkade and Kahneman, 1998; Dunn et al., 2003), according to which price partitioning diverts attention away from the overall price. The latter follows from the assumption that consumers might overlook non-salient prices, such as a 3D surcharge hidden in a footnote.

Hypothesis 1. *The likelihood of* selecting tickets *for a 3D movie is lowest in Inclusive, at an intermediate level in Partitioned, and highest in Shrouded.*

Since in all treatments the full price is transparently presented on the *Payment* screen, and since the purchase process is short and easy to cancel, and since the surcharge is very sizable (at least in relative terms), we expect that the likelihood of actually completing a purchase process is independent of the price presentation. Also, other frictions (e.g., social image concerns or the attachment effect) are arguably negligible in our experimental context, so that consumers in *Partitioned* and *Shrouded* should *not* be more likely to buy tickets after learning the total price.

Hypothesis 2. *The likelihood of* buying tickets *for a 3D movie does not vary across treatments*.

At this point, it is important to highlight that our hypotheses are also consistent with models that do not assume inattention on the consumer side. Given the costless nature of price discovery in our setup, a fully attentive consumer might simply initiate more purchase processes in *Shrouded* – without buying more often – to learn the full price. Our experimental design is not made to distinguish between different mechanisms consistent with the two hypotheses.

Discussion of our design. From a methodological perspective, our experimental design has three advantages compared to previous studies, such as Chetty et al. (2009) or Blake et al. (2018). First, we assigned the treatments randomly based on a unique user ID, so that our treatment effects are identified as accurately as in a laboratory setting. Blake et al. (2018), in contrast, randomize at the cookie level. However, if consumers access the site with different devices or delete cookies regularly and are therefore reassigned to a different treatment, this could be problematic.[9] Second, we observe not only aggregate revenues, but individual decisions throughout the whole purchase process, which allows us to compare a consumer's behavior inside a given *price frame* (on the *Shopping* screen) to her behavior outside of the frame (on the *Payment* and *Confirmation* screens). Third, we tracked the consumers' purchase history over the course of the experiment, so that we can also analyze long-term salience effects.

3. Empirical Analysis of Shopping Behavior

Data. Our intervention ran from 24 April 2017 until 14 January 2018. During the treatment period, we tracked all initiated purchase processes in the cinema's online store at the level of an individual consumer. Our sample includes all 34,902 consumers who initiated at least one purchase for a 3D movie during our intervention. We also analyze how the demand of these consumers for 2D movies was affected. Yet, we exclude consumers who were only interested in 2D movies and never initiated a purchase process for a 3D show.

Descriptives and randomization check. Table 1 provides a first overview of how shopping behavior varies across the different treatments: in Panel A, we report results for a consumer's first initiated purchase process for a 3D movie, while in Panel B we aggregate all initiated purchases for 3D movies over the nine months of the intervention. Consistent with Hypothesis 1, the share of consumers who select tickets, when initiating a purchase process for the first time, is smallest in *Inclusive*, at an intermediate level in *Partitioned*, and largest in *Shrouded*. A similar picture arises when taking all initiated purchases for 3D movies into account. In addition, we observe that the share of completed purchase processes does not vary by much across treatments, neither in Panel A nor in Panel B, which is consistent with Hypothesis 2. In Panel A, we further distinguish between purchases that take place immediately and purchases that take place at some later point in time. The latter takes into account that, after canceling the first initiated purchase process, a consumer might come back at some later point in time to buy tickets for the exact same 3D show that she clicked on first during our intervention. Indeed, across all three treatments, a substantial share of consumers does not buy immediately, but comes back later to do so: while between 49% (in *Inclusive*) and 55% (in *Shrouded*) of the

[9] Some evidence suggests that a substantial share of people delete their cookies regularly (see, for instance, the report at https://www.comscore.com/Insights/Press-Releases/2007/04/comScore-Cookie-Deletion-Report, accessed on 9 October 2020). As an alternative to assigning treatments via cookies, one may think of treatment assignments that are based on IP addresses. Before our intervention, we checked that the IP address of customers with the same user ID often changes: already within two weeks, around 20% of those consumers who clicked at least two times on a 3D movie visited the online store with different IP addresses. Thus, we decided against treatment randomizations based on cookies and IP addresses.

consumers cancel their first initiated purchase process for a 3D show, slightly more than 50% eventually buy tickets for the exact same show. Overall, the data on completed purchases imply that consumers in *Shrouded* are more likely to cancel the purchase process at the checkout.

Table 1. *Descriptive statistics on initiated and completed purchases for 3D movies.*

Panel A: First Initiated Purchase	Absolute Frequencies			Relative Frequencies		
	Inclusive	Partitioned	Shrouded	Inclusive	Partitioned	Shrouded
Select tickets	5,285	5,391	5,969	45.67%	46.34%	51.03%
Complete purchase						
- Immediately	3,931	3,853	3,943	33.97%	33.12%	33.71%
- Eventually	6,002	5,961	6,069	51.87%	51.24%	51.88%
# Consumers	11,571	11,633	11,698	-	-	-
Panel B: All Initiated Purchases	Absolute Frequencies			Relative Frequencies		
	Inclusive	Partitioned	Shrouded	Inclusive	Partitioned	Shrouded
Select tickets	13,396	13,645	15,673	39.86%	41.77%	46.06%
Complete purchase	10,238	10,115	10,300	30.46%	30.96%	30.27%
# Initiated Purchases	33,606	32,667	34,027	-	-	-

To test for our identifying assumption of random treatment allocation, we performed several randomization checks. Using a χ^2-test, we cannot reject the null hypothesis of a uniform distribution of consumers across treatments (p-value = 0.707). Also, when taking observables, such as the month of the first initiated purchase process for a 3D movie during our intervention (p-value = 1.000, X^2-test) or the 3D movie first clicked on (p-value = 0.931, X^2-test), into account, we cannot reject the null hypothesis of random treatment allocation. This suggests that the randomization of treatments worked properly.

Empirical strategy. Our analysis is divided in two parts: First, we look at the effects of our treatments on the likelihood of selecting and/or buying tickets when initiating a purchase process for a 3D movie for the first time. Second, we aggregate shopping behavior over all initiated purchase processes during the nine months of our intervention, which allows us to test for long-term salience effects. Table 2 summarizes our main dependent variables of interest.

Table 2. *Overview of the main dependent variables.*

	First initiated purchase	**All initiated purchases**
Ticket selection	$Select_i$: a binary indicator, which takes a value of one if consumer i selects tickets, and a value of zero otherwise.	# $Select_i$: a count variable, which counts how often consumer i selected tickets for a 3D movie during the intervention period.
Purchases	$Purchase_i$: a binary indicator, which takes a value of one if consumer i buys (at some point), and a value of zero otherwise.[10]	# $Purchase_i$: a count variable, which counts how often consumer i bought tickets for a 3D movie during the intervention period.

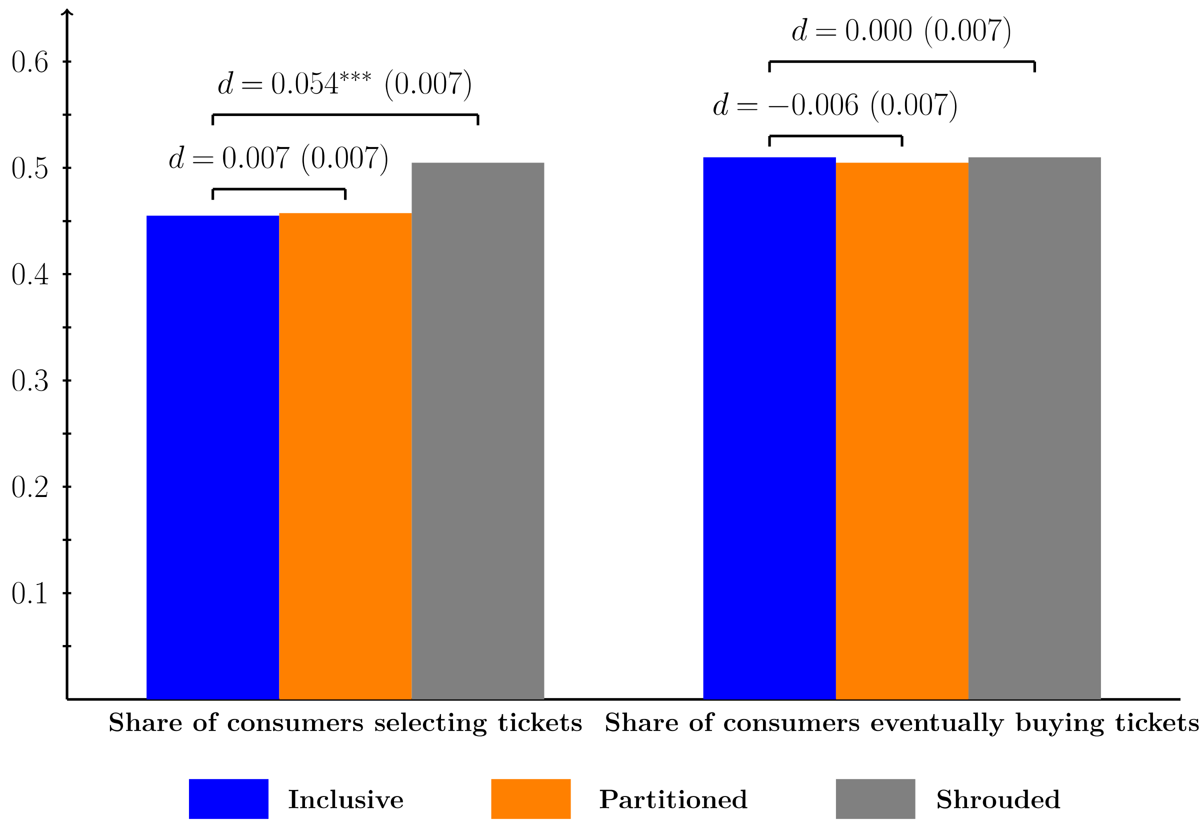
When looking at the first initiated purchase process for a 3D movie, the treatment allocation is random (see the randomization checks above), so that the average treatment effects on the probability of selecting and to purchase tickets can be estimated using OLS. When aggregating behavior over all initiated purchases during the nine months of our intervention period, it is important to keep in mind that the estimates of the average treatment effects regarding ticket selection might be biased due to differential attrition across treatments: the total number of initiated purchase processes during the nine months differs across treatments (see the last line of Table 1), which could be a systematic treatment effect and therefore potentially problematic. As we show in Appendix B.3, however, our naively estimated average treatment effects regarding ticket selection are robust to imposing worst-case scenarios, in which we assume that all "missing" purchase processes due to differential attrition go against our hypotheses. If we analyze how our treatments affect the number of purchases over the nine months, differential attrition is not an issue, but a crucial part of the potential treatment effects we are interested in.

Salience affects ticket selection, but not purchases. To begin with, we consider only a consumer's first initiated purchase process. Here, we find that shrouding the 3D surcharge significantly increases the probability of a consumer selecting tickets by 5.4 percentage points relative to a situation where the surcharge-inclusive price is presented right from the beginning

[10] If a consumer cancels her first initiated purchase process for a 3D movie, but then comes back later to buy tickets eventually for the exact same show, we set $Purchase_i$ to one. However, as we verify in Appendix B.1, our results do not depend on whether we make this adjustment or not.

(see Figure 3 and Table 3). This finding is consistent with Hypothesis 1. Partitioning the total price into its two components, in contrast, does not have a significant effect on the average probability of selecting tickets, which is inconsistent with Hypothesis 1. Moreover, consistent with Hypothesis 2, we observe that neither shrouding nor partitioning the 3D surcharge have a significant effect on the average probability of purchasing tickets for a 3D movie (see Figure 3 and Table 4). This implies that consumers in *Shrouded* differentially drop out of the purchase process once they are presented the full price (including the surcharge) on the *Payment* screen.

Figure 3. *Main findings regarding the first initiated purchase process.*



Notes on Figure 3: *The figure depicts, for the first initiated purchase process for a 3D movie, the share of consumers who selected and bought (potentially at a later point in time) tickets, separately for the three different treatments (Table 1). The estimated treatment effects refer to the first column of Table 3 (ticket selection) and Table 4 (completed purchases). We provide the corresponding standard errors in parentheses. ***: Significant at 1%.*

Table 3. *Treatment effects on ticket selection for the first initiated purchase process.*

Parameter	Select	Select	Select	Select	Select
Partitioned	0.007	0.007	0.006	0.004	0.008
	(0.007)	(0.006)	(0.011)	(0.011)	(0.009)
Shrouded	0.054***	0.053***	0.053***	0.056***	0.053***
	(0.007)	(0.006)	(0.011)	(0.011)	(0.009)
3D Substitute	-	-	-0.009	-	-
			(0.011)		
3D Sub x Partitioned	-	-	-0.004	-	-
			(0.014)		
3D Sub x Shrouded	-	-	-0.001	-	-
			(0.014)		
Blockbuster	-	-	-	0.158	-
				(0.134)	
Blockbuster x Partitioned	-	-	-	0.005	-
				(0.013)	
Blockbuster x Shrouded	-	-	-	-0.005	-
				(0.013)	
Weekend	-	-	-	-	0.011
					(0.013)
Weekend x Partitioned	-	-	-	-	-0.003
					(0.013)
Weekend x Shrouded	-	-	-	-	-0.000
					(0.013)
Movie FE	no	yes	yes	yes	yes
Time FE	no	yes	yes	yes	yes
2D Substitute Dummy	no	yes	yes	yes	yes
# Observations	34,902	34,902	31,101	34,902	34,902

Notes on Table 3: *The table presents the results of OLS regressions. The dependent variable $Select_i$ is defined in Table 2. The independent variables of interest are treatment indicators (and Inclusive serves as the base category). In the second column, we add movie and time fixed effects, as well as a control for whether a 2D substitute is available in the same cinema at broadly the same time. In columns three to five, we further interact the treatment indicators with either an indicator of whether the same 3D movie runs at broadly the same time in another cinema in the same city (third column), an indicator of a blockbuster movie (fourth column), or an indicator of weekends (fifth column). Standard errors are provided in parentheses. ***: Significant at 1%.*

Table 4. *Treatment effects on purchase decisions for the first initiated purchase process.*

Parameter	**Purchase**	**Purchase**	**Purchase**	**Purchase**	**Purchase**
Partitioned	-0.006	-0.006	-0.001	-0.001	-0.009
	(0.007)	(0.007)	(0.011)	(0.011)	(0.009)
Shrouded	0.000	-0.000	-0.004	0.007	0.002
	(0.007)	(0.006)	(0.011)	(0.011)	(0.009)
3D Substitute	-	-	0.000	-	-
			(0.012)		
3D Sub x Partitioned	-	-	-0.013	-	-
			(0.014)		
3D Sub x Shrouded	-	-	0.009	-	-
			(0.014)		
Blockbuster	-	-	-	0.032	-
				(0.135)	
Blockbuster x Partitioned	-	-	-	-0.009	-
				(0.014)	
Blockbuster x Shrouded	-	-	-	-0.011	-
				(0.013)	
Weekend	-	-	-	-	-0.005
					(0.013)
Weekend x Partitioned	-	-	-	-	0.006
					(0.013)
Weekend x Shrouded	-	-	-	-	-0.004
					(0.013)
Movie FE	no	yes	yes	yes	yes
Time FE	no	yes	yes	yes	yes
2D Substitute Dummy	no	yes	yes	yes	yes
# Observations	34,902	34,902	31,101	34,902	34,902

Notes on Table 4: *The table presents the results of OLS regressions. The dependent variable* $\mathtt{Purchase}_i$ *is defined in Table 2. The independent variables of interest are treatment indicators (and Inclusive serves as the base category). In the second column, we add movie and time fixed effects, as well as a control for whether a 2D substitute is available in the same cinema at broadly the same time. In columns three to five, we further interact the treatment indicators with either an indicator of whether the same 3D movie runs at broadly the same time in another cinema in the same city (third column), an indicator of a blockbuster movie (fourth column), or an indicator of weekends (fifth column). Standard errors are provided in parentheses.*

As illustrated in Tables 3 and 4, the estimated treatment effects on the probability of selecting and buy tickets for a 3D movie are robust to adding several controls. The specifications in the second columns of the respective tables replicate the baseline findings while controlling for movie and time fixed effects (where the latter include month, day of the week, and time of the day FEs) and for whether a 2D show of the same movie runs within +/- 1 hour in the same cinema. We estimate further specifications in which we interact the treatment indicators with either an indicator of whether the same 3D movie runs at broadly the same time (i.e. +/- 1 hour) in another cinema in the same city (third column),[11] an indicator of a blockbuster movie (fourth column),[12] or an indicator of weekends (fifth column). The estimated average treatment effects are stable across all specifications: Relative to *Inclusive*, the average probability of selecting tickets for a 3D movie significantly increases by at least 5.2 percentage points in *Shrouded*, but does not differ significantly in *Partitioned*. The estimated treatment effects on the likelihood of purchasing tickets for a 3D movie are all statistically and economically insignificant.

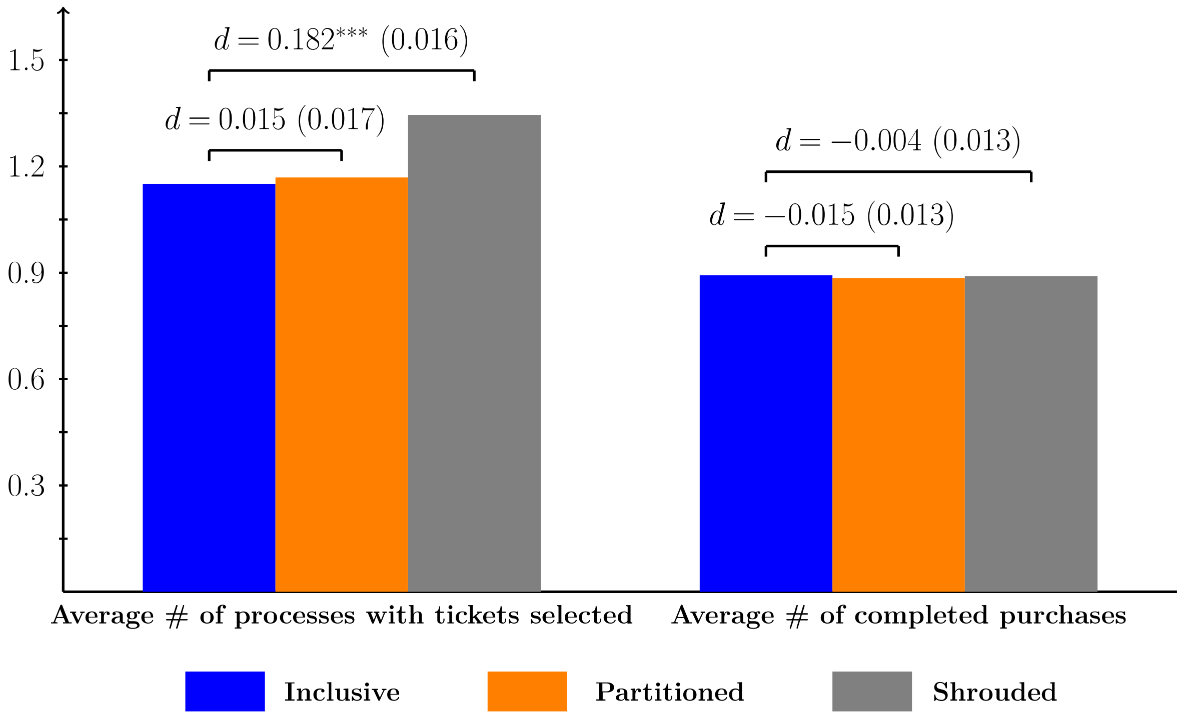
When aggregating shopping behavior over all initiated purchase processes during the nine months of our intervention, we find similar patterns: The average number of purchase processes for which a consumer selected tickets on the *Shopping* screen and then proceeded to the *Payment* screen is significantly larger in *Shrouded* than it is in *Inclusive*, but not significantly different between *Partitioned* and *Inclusive* (see Table B.2 in the Appendix).[13] Both findings are robust to imposing worst-case scenarios which assume that all "missing" purchase processes due to differential attrition in either treatment go against our hypotheses (see the analysis provided in Appendix B.3). Moreover, we observe that the average number of completed purchase processes over the entire intervention period does not vary significantly across treatments (Table B.3 in the Appendix), which is again consistent with Hypothesis 2. Our main findings on the long-term salience effects are summarized in Figure 4.

[11] Note that the number of observations is reduced compared to our baseline regressions, as we do not have information on the schedules of other cinemas in the same city for each day of our intervention period.

[12] We classified a movie as a blockbuster if it belongs to the top 25% of movies in our sample in terms of worldwide revenue (revenue data is collected from http://www.boxofficemojo.com, accessed on 18 July 2018).

[13] As we verify in Appendix C, the observed salience effects on the likelihood of selecting tickets on the *Shopping* screen persist over time. Precisely, when using, for each consumer, her second initiated purchase process for a 3D movie during our intervention period, we find similar (even larger) treatment effects on the likelihood of selecting tickets for a 3D movie. Even for consumers who come back within one hour after their first initiated purchase process for a 3D movie and who click on the exact same film as before, the likelihood of selecting tickets is still significantly larger in *Shrouded* than in *Inclusive* (see Table C.2 in the Appendix), while the likelihood of buying tickets does not vary significantly across treatments (see Table C.4).

Figure 4. *Main findings when aggregating behavior over all initiated purchases.*



Notes on Figure 4: *The figure depicts the number of initiated purchase processes for which the consumer selected tickets and actually completed the purchase, separately for the different treatments (Table 1). The estimated treatment effects refer to the first column of Table B.2 (ticket selection) and Table B.3 (completed purchases) in the Appendix. We provide the corresponding standard errors in parentheses. ***: Significant at 1%.*

Salience has no effect on repeat purchases. The panel structure of our data allows us to analyze in more detail whether shrouding or partitioning the 3D surcharge has adverse effects on the long-term demand for 3D movies. Consumers might, for instance, be annoyed by a manipulation of the price presentation that tricked them into buying, and therefore might refrain from a repeat purchase. The analysis of repeat purchases complements the preceding analysis of long-term demand by focusing on potential differences in the demand structure across treatments that go beyond just the average number of purchases.

First, we consider the subsample of consumers who bought tickets for a 3D movie at least once (i.e., 22,405 out of 34,902 consumers), and we ask whether the average likelihood of a second purchase for a 3D movie and/or the average number of repeat purchases for 3D movies vary across treatments. As illustrated in Table 5, we find that neither shrouding nor partitioning the 3D surcharge has a significant effect on the likelihood of a repeat purchase or the number of repeat purchases, which supports the observation that not only short-term, but also long-term demand for 3D movies is insensitive to the price presentation.

Table 5. *Repeat purchases of 3D movies.*

Parameter	**Repeat Purchase**	**# Repeat Purchases**
Partitioned	0.001	-0.000
	(0.007)	(0.015)
Shrouded	-0.007	-0.013
	(0.007)	(0.015)
Model	OLS	OLS
# Observations	22,405	22,405

Notes on Table 5: *The table presents the results of OLS regressions. The dependent variable in the first column is a binary indicator of whether a consumer, who has bought at least once, buys again. The dependent variable in the second column is the number of repeat purchases of such a consumer. The independent variables are treatment indicators (and Inclusive serves as the base category). Standard errors are provided in parentheses.*

The preceding estimates could be biased, however, because, conditional on having bought at least once, treatment allocation is not necessarily random anymore. To address this problem (at least partially), we go back to the full sample, including all 34,902 consumers, where treatment allocation is random, and we study in more detail how our treatments affect the distribution – not only its first moment (as in Figure 4) – of the number of purchases over the intervention period. Precisely, on the full sample including all consumers, we regress a binary indicator of whether a consumer has bought, at least k times, $k \in \{1, 2, 5, 10\}$, tickets for a 3D movie on the treatment indicators. As depicted in Table 6, we do not find any significant treatment effect of shrouding the 3D surcharge. When neglecting the problem of multiple-hypotheses testing, partitioning the price into its two components has a weakly significant negative effect on the average probability of buying tickets for a 3D movie (p-value = 0.081) at least once. While certainly not perfect, the results presented in Table 6 strongly suggest that the distribution of purchases does not differ significantly across treatments, which again confirms our observation that not only short-term, but also long-term demand for 3D movies is insensitive to the price presentation.

Table 6. *Share of consumers who bought tickets for a 3D movie at least k times.*

Parameter	At least 1	At least 2	At least 5	At least 10
Partitioned	-0.011*	-0.002	-0.001	-0.000
	(0.006)	(0.005)	(0.001)	(0.000)
Shrouded	0.003	-0.004	-0.001	-0.000
	(0.006)	(0.005)	(0.001)	(0.000)
# Observations	34,902	34,902	34,902	34,902

Notes on Table 6: *The table presents OLS regressions with the dependent variable being binary indicators of a consumer buying at least k times tickets for a 3D movie. The independent variables are treatment indicators (where Inclusive serves as the base category). Standard errors are provided in parentheses. *: Significant at 10%.*

Revenues are unaffected by salience. So far, we have seen that our treatments have no effect on the number of purchases for 3D movies. In the Appendix, we further verify that our treatments do not affect the average number of purchased tickets for 3D shows (Table B.4). Moreover, not only is the demand for 3D movies insensitive to the presentation of prices, but the demand for 2D movies does not vary significantly either across treatments. This holds for both the number of purchases as well as the number of purchased tickets for 2D movies (see Table B.5 in the Appendix). From that, we conclude that our treatments do not affect the cinema's revenues, at least not for fixed prices. Table 7 provides the corresponding regression results.

Table 7. *Average per-customer revenue over the intervention period.*

Parameter	2D Revenue	3D Revenue	Total Revenue
Partitioned	0.310	0.205	0.514
	(0.460)	(0.515)	(0.759)
Shrouded	0.603	-0.012	0.591
	(0.459)	(0.514)	(0.758)
# Observations	34,902	34,902	34,902

Notes on Table 7: *The table presents the results of OLS regressions. The dependent variable is the per-customer revenue for 2D movies (first column) or 3D movies (second column) or all movies (third column), measured in Euros, over the nine-month intervention period. The independent variables are treatment indicators (and Inclusive serves as the base category). Standard errors are provided in parentheses.*

A simple back-of-the-envelope calculation shows that, with a 95% probability, shrouding the 3D surcharge for all consumers in *Inclusive* would increase the cinema's revenues by less than

$$\frac{11{,}571 \text{ consumers in Inclusive} \times 2.077 \text{ Euro per consumer}}{9 \text{ months}} = 2{,}573.90 \text{ Euro per month,}$$

on average, which is approximately 1.37% of the cinema's average monthly revenues from selling movie tickets via the online store. Hence, even in the best case, the increase in profits due to shrouding the 3D surcharge, when keeping the price level fixed, is small.

4. Conclusion

To investigate the effects of price salience on online shopping, we present the results of a field experiment with more than 34,000 consumers of a German cinema. We test for the effects of shrouding and partitioning of surcharges, two practices that are frequently applied by companies to increase sales (see Ellison and Ellison, 2009, or Heidhues and Kőszegi, 2018). Our experimental design allows us to disentangle the effects of price partitioning or shrouding on the likelihood of selecting and purchasing products (in our case, movie tickets).

We find that shrouding a 3D surcharge substantially increases the probability of a consumer selecting tickets for a 3D movie, compared to a presentation where the surcharge is included in the displayed price right from the beginning. For actual purchases, we find no treatment differences at all, that is, neither partitioning nor shrouding the 3D surcharge have a positive effect on the likelihood of completing a purchase. As a consequence, we find no effect of shrouding on the cinema's profits.

We regard our results as an important complement to the existing empirical literature on salience effects. In fact, we show that shrouding or partitioning surcharges alone can be inadequate instruments to trick consumers into buying more when the surcharge is large and when there are no frictions that prevent the consumer from learning the full price and from canceling an initiated purchase process. In this sense, our experimental findings could provide a rationale for why many online shops (e.g., travel companies) make it time-consuming to complete a purchase process after initiation; namely, as this may introduce frictions that prevent consumers from canceling an initiated purchase.

While we have established boundaries of salience effects that are novel to the literature, our study is not designed to pin down the precise factors that are necessary for shrouding of surcharges to affect demand. To answer this question in future work, lab experiments are better suited than field experiments, as in the lab the size of the surcharge as well as various frictions in the process of discovering prices or canceling purchases (e.g., observability of cancellations by others, length of the purchase process, re-optimization costs) can be varied systematically.

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Appendix A: Overview of the Related Literature

	Field / Lab	Products	Shrouded Component and sum	Additive (A)/ multiplicative (M) surcharge	Sample size	Effect size due to shrouding	Inclusive price displayed prior to purchase	Initial effect	Delay till full price is shown	If full price is presented: what are cancellation costs?	Prior price format	Selling Mechanism	Suggested mechanism
This study	Field	Movie tickets	3D surcharge (about 40%)	A	N=34,902 subjects in 3 treatments	No revenue effect	Yes	Stronger	One screen	None	Inclusive	Fixed price	-
Morwitz et al. (1998)	Lab	Pennies	Buyer's premium of 15% of the bid	M	N=199 subjects, divided over 2 treatments	11% decrease in perceived costs	No	-	-	-	None	Auction	Inattention to surcharges
Hossain and Morgan (2006)	Field	CDs, Xbox Games	Shipping cost (about 4 Euro)	A	N=80 product auctions, divided over 8 treatments	On average about 16% increase in revenue	No	-	-	-	Diverse	Auction	Loss aversion, Salience
Chetty et al. (2009)	Field	Cosmetics	Sales tax (7.4%)	M	19,764 quantity-week-store combinations	8% increase in revenue	Yes	N/A	N/A	Social costs, re-optimization costs	Exclusive	Fixed price	Salience/ Inattention to surcharges
Finkelstein (2009)	Field	Road usage	Toll	A	N=5,079 facility-years	20-40% increase in spending	No	-	-	-	Inclusive and Cash	Fixed price	Salience/ Inattention to surcharges
Brown et al. (2010)	Field	Ipod Shuffle	Shipping cost (11 or 14 Euro)	A	N=76 product auctions, 6 treatments in Taiwan (n=6 in each) and 4 in Ireland (n=10 in each)	6% increase in revenue	No	-	-	-	Shrouding	Auction	Inattention to surcharges
Feldman and Ruffle (2015)	Lab	Junk food, school supply, personal hygiene	Tax (16% VAT)	M	N=120 subjects, divided over two treatments	25% increase in spending	Yes	Stronger	One screen	Confirmation bias, re-optimization costs	Outside the lab, in Israel both in- and exclusive prices are usual	Fixed price	Confirmation bias
Feldman et al. (2018)	Lab	Household items	Tax (8% and 22%)	M	N=227 subjects, 2 high- and low-tax treatments and 2 controls	On average 9% increase in spending	Yes	Stronger	One screen	Confirmation bias, re-optimization costs	Outside the lab, both exclusive prices are usual	Fixed price	Confirmation bias
Taubinsky and Rees-Jones (2018)	Lab-in-field	Household items	Sales tax (approx. 7% and 21%)	M	N=2,998 individuals	25% implicit weight on taxes	No	-	-	-	Outside the lab, both exclusive prices are usual	BDM to elicit WTP	Salience/ Inattention to surcharges
Blake et al. (2018)	Field	Tickets for shows and concerts	Buyer fee (15%) + shipping charge	M + A	Not reported	20% increase in revenue	Yes	Stronger	One screen	Experience of loss, re-optimization costs	Inclusive (but most customers are new to site)	Fixed price	Salience/ Inattention + Frictions (Loss aversion, re-optimization costs)

Appendix B: Additional Regression Analyses

B.1: First Initiated Purchase Process for a 3D Movie

Table B.1. *Treatment effects on purchase decisions for the first initiated purchase process.*

Parameter	Purchase	Purchase	Purchase	Purchase	Purchase
Partitioned	-0.009	-0.008	-0.004	-0.006	-0.014
	(0.006)	(0.006)	(0.011)	(0.010)	(0.009)
Shrouded	-0.003	-0.003	0.002	0.000	-0.009
	(0.006)	(0.006)	(0.011)	(0.010)	(0.009)
3D Substitute	-	-	-0.007	-	-
			(0.011)		
3D Sub x Partitioned	-	-	-0.010	-	-
			(0.013)		
3D Sub x Shrouded	-	-	-0.008	-	-
			(0.013)		
Blockbuster	-	-	-	0.298**	-
				(0.127)	
Blockbuster x Partitioned	-	-	-	-0.004	-
				(0.013)	
Blockbuster x Shrouded	-	-	-	-0.005	-
				(0.013)	
Weekend	-	-	-	-	0.003
					(0.012)
Weekend x Partitioned	-	-	-	-	0.011
					(0.012)
Weekend x Shrouded	-	-	-	-	0.011
					(0.012)
Movie FE	no	yes	yes	yes	yes
Time FE	no	yes	yes	yes	yes
2D Substitute Dummy	no	yes	yes	yes	yes
# Observations	34,902	34,902	31,101	34,902	34,902

Notes to Table B.1: *The table presents the results of OLS-regressions. The dependent variable is a binary indicator of whether a consumer completes the first initiated purchase process for a 3D movie. This is different from the analysis presented in Table 4, where we further take into account whether the consumer comes back later to buy tickets for the exact same show. The independent variables of interest are again treatment indicators (whereby Inclusive serves as the base category). We subsequently add the same set of controls as we do in the main text. Standard errors are provided in parentheses. **: Significant at 5%.*

B.2: Aggregating Behavior Over All Initiated Purchase Processes

In this subsection, we consider all initiated purchase processes during the 9-months-period of our intervention. First, we study the treatment effects on the average number of purchase processes for 3D movies with tickets being selected (see the left panel of Figure 4). In principle, we might be worried about selection effects due to differential attrition, but, as we argue in Appendix B.3, selection turns out not to be an issue here. Second, we study the treatment effects on the average number of purchases (see the right panel of Figure 4) and purchased tickets for 3D as well as 2D movies. Here, selection is not a threat to identification, but a crucial part of the effect we are interested in, as not entering the online store can be interpreted as not buying.

Ticket selection. To address the question of whether the salience of prices affects ticket selection also in the long run, we regress the number of purchase processes for 3D movies with tickets being selected on treatment indicators. The first column of Table B.2 presents the regression results underlying Figure 4, which is shown in the main text: while partitioning the price into its two components has again no significant effect on ticket selection, shrouding the 3D surcharge significantly increases the average number of purchase processes for which tickets are selected by 0.182. To account for the data structure, we also estimate count models with the same result.[15] Precisely, we present the results of a Negative Binomial (NEGBIN) model with (in the second column) and without (in the third column) exposure.[16]

Table B.2. *Treatment effects on ticket selection for 3D movies over the intervention period.*

Parameter	**# Select**	**# Select**	**# Select**
Partitioned	0.015	0.013	0.035***
	(0.017)	(0.013)	(0.013)
Shrouded	0.182***	0.146***	0.138***
	(0.016)	(0.013)	(0.012)
Model	OLS	NEGBIN	NEGBIN
Exposure	-	no	yes
# Observations	34,902	34,902	34,902

Notes to Table B.2: *Results of regressing the number of purchase processes for 3D movies with tickets being selected (Table 2) on treatment indicators (whereby Inclusive serves as the base category), using OLS and NEGBIN models with and without exposure. Standard errors are provided in parentheses. ***: Significant at 1%.*

[15] For all treatments, we can reject the null hypotheses of mean-variance equivalence against the alternatives of overdispersion. Given these patterns, a Negative Binomial model is more appropriate than a Poisson model.

[16] As the exposure variable, we use for each consumer her overall number of initiated purchases for 3D movies.

Purchases. First, we regress the number of purchases for 3D movies over the intervention period on treatment indicators. The first column of Table B.3 presents the regression results underlying Figure 4: neither partitioning nor shrouding of the 3D surcharge has a significant effect on the average number of purchases for 3D movies over the intervention period.[17] Second, we regress the number of purchased tickets for 3D movies on treatment indicators, and again we do not find any significant treatment effect (see Table B.4).

Table B.3. *Treatment effects on purchases for 3D movies over the intervention period.*

Parameter	**# Purchases**	**# Purchases**	**# Purchases**
Partitioned	-0.015	-0.017	0.003
	(0.013)	(0.014)	(0.015)
Shrouded	-0.004	-0.005	-0.009
	(0.013)	(0.014)	(0.015)
Model	OLS	NEGBIN	NEGBIN
Exposure	-	no	yes
# Observations	34,902	34,902	34,902

Notes to Table B.3: *Results of regressing the number of purchases for 3D movies (Table 2) on treatment indicators (whereby Inclusive serves as the base category), using OLS and NEGBIN models with and without exposure. Standard errors are provided in parentheses.*

Table B.4. *Treatment effects on purchased tickets for 3D movies over the intervention period.*

Parameter	**# Tickets**	**# Tickets**	**# Tickets**
Partitioned	0.017	0.007	0.011
	(0.036)	(0.016)	(0.016)
Shrouded	0.001	0.000	0.004
	(0.036)	(0.016)	(0.016)
Model	OLS	NEGBIN	NEGBIN
Exposure	-	no	yes
# Observations	34,902	34,902	34,902

Notes to Table B.4: *Results of regressing the number of purchased tickets for 3D movies on treatment indicators (whereby Inclusive serves as the base category), using OLS and NEGBIN models with and without exposure. Standard errors are provided in parentheses.*

[17] To account for the data structure, we also estimate count models. Again, Negative Binomial models are more appropriate than Poisson models. The results are basically the same as for the OLS regression.

Third, we look into potential treatment effects on the number of purchases and number of purchased tickets for 2D movies. As it is the case for 3D movies, we neither find significant treatment effects on the number of purchases nor the number of purchased tickets (Table B.5).

Table B.5. *Treatment effects on purchases for 2D movies over the intervention period.*

Parameter	**# Purchases**	**# Purchases**	**# Tickets**	**# Tickets**
Partitioned	-0.001	-0.002	0.026	0.016
	(0.018)	(0.024)	(0.046)	(0.030)
Shrouded	0.010	0.015	0.052	0.032
	(0.018)	(0.024)	(0.046)	(0.030)
Model	OLS	NEGBIN	OLS	NEGBIN
Exposure	-	no	-	no
# Observations	34,902	34,902	34,902	34,902

Notes to Table B.5: *Results of regressing the number of purchases and purchased tickets for 2D movies, respectively, on treatment indicators (whereby Inclusive serves as the base category), using OLS and NEGBIN models with and without exposure. Standard errors are provided in parentheses.*

B.3: Worst-Case Scenarios for the Treatment Effects on Ticket Selection

To address potential selection issues and to assess the validity of the naively estimated treatment effects on the average number of purchase processes with tickets being selected, as presented in Table B.2, we impose worst-case scenarios, by assuming that all ”missing” initiated purchase processes in either of the treatments go against our hypotheses.

First, we consider the effect of partitioning the total price into its two components. For that, we assume that all missing initiated purchase processes in *Partitioned* go against Hypothesis 1. Over the nine months of our intervention, consumers in *Partitioned* have initiated 939 fewer purchase processes for 3D movies than consumers in *Inclusive* (see Table 1). The most conservative way to test for the average treatment effect of price partitioning on ticket selection is to assume that *all* missing purchase processes in *Partitioned* would have been drop-outs on the *Shopping* screen. Then we add these missing drop-outs to those consumers with the highest rates of selecting tickets and the smallest numbers of initiated purchases for 3D movies[18], as

[18] There are more than 939 consumers in *Partitioned* with only a single initiated purchase process for a 3D movie and no drop-out on the *Shopping* screen (i.e., they actually selected tickets and proceeded to the *Payment* screen). Among these consumers, we chose randomly and increased the number of initiated purchase processes for 3D movies by one without changing the number of processes for which tickets have been selected. We use this adjusted number of initiated purchase processes for 3D movies to estimate a lower bound on the average treatment effect of price partitioning on the number of purchase processes with tickets being selected.

this maximizes the decrease in the average ticket-selection rate.[19] We then estimate an OLS regression and Negative Binomial models with and without exposure (see Table B.3).

Table B.6. *Lower-bound estimation of ticket selection in Partitioned (worst-case scenario).*

Parameter	**# Select**	**# Select**	**# Select**
Partitioned	0.015	0.013	0.003
	(0.016)	(0.013)	(0.013)
Model	OLS	NEGBIN	NEGBIN
Exposure	-	no	yes
# Observations	23,204	23,204	23,204

Notes to Table B.6: *Results of worst-case scenario in which we regress the adjusted number of initiated purchase processes for 3D movies on an indicator for Partitioned, using OLS and NEGBIN models with and without exposure. Standard errors are provided in parentheses.*

The results confirm that price partitioning does not have a significant effect on ticket selection, but it also suggests that partitioning does not decrease the average number of purchase processes with tickets being selected, which would be the exact opposite of Hypothesis 1.

Second, we consider the effect of shrouding the 3D surcharge in more detail. Over the nine months of our intervention, the consumers in *Shrouded* have initiated 421 more purchase processes for 3D movies than consumers in *Inclusive*. In order to obtain a lower bound on the average treatment effect of shrouding on ticket selection, we assume that consumers in *Inclusive* had initiated 421 more purchase processes for 3D movies in all of which they selected tickets and proceeded to the *Payment* screen. The most conservative way to allocate these missing purchase processes in *Inclusive* is to add them to those consumers with the lowest ticket-selection rate and the smallest numbers of initiated purchase processes for 3D movies[20], as this maximizes the increase in the average ticket-selection rate.[21] Given these assumptions, we estimate an OLS regression as well as Negative Binomial models with and without exposure (see Table B.7). As it is the case for *Partitioned,* also for *Shrouded* the worst-case scenario

[19] For illustrative purposes, denote as D_i the number of drop-outs on the *Shopping* screen and as N_i the number of initiated purchase processes for 3D movies by consumer i. In addition, let $s_i := (N_i - D_i)/N_i$ be the rate with which consumer i selects tickets for a 3D movie. Increasing both D_i and N_i by one, so that $N_i - D_i$ stays constant, results in a decrease of the ticket-selection rate by $s_i/(N_i + 1)$, which increases in s_i and decreases in N_i.

[20] There are more than 421 consumers in *Inclusive* with only a single initiated purchase process for a 3D movie who further dropped out on the *Shopping* screen. Among these consumers, we chose randomly and increased the number of initiated purchase processes for 3D movies as well as the number of purchase processes with tickets being selected by one.

[21] Using the notation from before, we conclude that increasing the number of initiated purchase processes for 3D movies, N_i, as well as the number of processes with tickets being selected, $(N_i - D_i)$, by one increases the ticket-selection rate by $(1 - s_i)/(N_i + 1)$, which decreases in s_i and in N_i.

confirms the naive estimates in Table B.2, both qualitatively and quantitatively: the average number of purchase processes with tickets being selected is significantly larger in *Shrouded* than in *Inclusive*, and the estimated treatment effect is still of economically relevant size.

Table B.7. *Lower-bound estimation of initiations in Shrouded (worst-case scenario).*

Parameter	**# Select**	**# Select**	**# Select**
Shrouded	0.146***	0.115***	0.118***
	(0.017)	(0.012)	(0.012)
Model	OLS	NEGBIN	NEGBIN
Exposure	-	no	yes
# Observations	23,269	23,269	23,269

Notes to Table B.7: *Results of worst-case scenario in which we regress the adjusted number of initiated purchase processes for 3D movies with tickets being selected on an indicator for Shrouded, using OLS and NEGBIN models with and without exposure. Standard errors are provided in parentheses. ***: Significant at 1%.*

Appendix C: Persistence of Salience Effects

We further ask whether our treatments still affect ticket selection and/or purchases when a consumer initiates a purchase process for a 3D movie for the second time. We distinguish two groups of consumers, depending on the timing of the second initiated purchase process: consumers who initiate the second purchase process *within 1 hour* after the first initiated purchase for a 3D movie and consumers who come back *at least 1 hour* after their first initiated purchase process for a 3D movie. We further distinguish between consumers who click on the *same film* as they did the first time and consumers who click on an *other film*.

Table C.1. *Distribution of consumers across treatments for the second initiated purchase.*

	Inclusive	**Partitioned**	**Shrouded**	**Total**	**p-value**
Full sample	11,571	11,633	11,698	34,902	-
Within 1 hour	3,760	3,815	3,941	11,516	0.360
- Same film	3,647	3,704	3,835	11,186	0.305
- Other film	113	111	106	330	0.853
At least 1 hour	2,804	2,774	2,809	8,387	0.864
- Same film	1,159	1,229	1,239	3,627	0.343
- Other film	1,645	1,545	1,570	4,760	0.151

Notes to Table C.1: *The last column presents the p-values of Fisher's exacts test with null hypotheses that the distribution over treatments in the respective subsample is the same as in the full sample.*

Importantly, when conditioning on a consumer's second initiated purchase for a 3D movie, the treatment allocation is not necessarily random anymore. But the fact that our treatments do not affect the number of repeat purchases for 3D movies (see Table 5) suggests that selection might not be a major issue. This is supported by the results of Fisher's exact tests with the null hypotheses that the distribution of consumers across treatments, conditional on the second initiated purchase, is identical to that in the full sample (see Table C.1). In the following, we first estimate treatment effects using OLS as if selection was not an issue. Subsequently, we again impose a worst-case scenario (at least for ticket selection) to address potential issues.

Ticket selection. To begin with, we consider the treatment effects on ticket selection. For consumers who come back within 1 hour after the first initiated purchase process, partitioning the surcharge does not have a significant effect on the average probability to put tickets in the shopping basket, which is in line with our results on the first initiated purchase process for a 3D movie. For consumers who come back at least 1 hour after their first initiated purchase process and click again on the same film, however, partitioning has a significant effect: consumers in *Partitioned* are, on average, 4.3 p.p. more likely to select tickets than consumers in *Inclusive*. As before, shrouding the 3D surcharge significantly (except for the subsample *within 1 hour, other film* with only few observations) increases the average probability of selecting tickets, by 6.3 to 7.4 p.p. depending on the subsample. Most notably, even for consumers who come back within 1 hour *and* click on the exact same film as they did the first time, the probability of selecting tickets is 6.1 p.p. higher in *Shrouded* than in *Inclusive* (see Table C.2).

Table C.2. *Treatment effects on ticket selection for the second initiated purchase process.*

Parameter	**Within 1 hour**			**At least 1 hour**		
	All	Same	Other	All	Same	Other
Partitioned	0.021*	0.021*	0.050	0.031**	0.043**	0.021
	(0.011)	(0.011)	(0.061)	(0.013)	(0.020)	(0.017)
Shrouded	0.063***	0.061***	0.101	0.070***	0.063***	0.074***
	(0.011)	(0.011)	(0.062)	(0.013)	(0.020)	(0.017)
Movie FE	yes	yes	no	yes	yes	yes
Time FE	yes	yes	no	yes	yes	yes
2D Substitute	yes	yes	no	yes	yes	yes
# Observations	11,516	11,186	330	8,387	3,627	4,760

Notes to Table C.2: *OLS-regressions with a binary indicator of whether a consumer selects tickets for the second initiated purchase process as dependent variable. The independent variables of interest are treatment indicators (whereby Inclusive serves as the base category). We add the same controls as in the main text, except for the* *subsample "within 1 hour, other film" with only few observations. Standard errors are provided in parentheses. *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.*

In order to address potential selection issues, we again impose worst-case scenarios by assuming that "missing" purchase processes in either of the treatments go against our hypotheses. Since partitioning the 3D surcharge has at best a weakly significant effect on the probability of selecting tickets, we focus here on the comparison between *Inclusive* and *Shrouded*. To obtain lower bounds on the estimated treatment effects in Table C.2, we equalize the number of consumers in the two treatments in the following way: If there are more consumers in *Inclusive*, then we randomly drop consumers from *Inclusive* who did not select tickets until the number of consumers is the same as in *Shrouded*. This is indeed the case for the subsamples *within 1 hour, other film* (7 consumers) and *at least 1 hour, other film* (75 consumers). If there are more consumers in *Shrouded*, then we randomly drop consumers from *Shrouded* who selected tickets until the number of consumers is the same as in *Inclusive*. This is indeed the case for the subsamples *within 1 hour* (181 consumers), *within 1 hour, same film* (188 consumers), *at least 1 hour* (5 consumers), and *at least 1 hour, same film* (80 consumers).

We find that, even in these worst-case scenarios, the effect of shrouding the 3D surcharge remains significant for all but one subsample. Only for consumers who come back at least 1 hour after their first initiated purchase process for a 3D movie and click on the same film as before, the average probability of selecting tickets is no longer significantly larger in *Shrouded* than in *Inclusive* (p-value = 0.088). Moreover, the shrouding effects in these worst-case scenarios are still of economically significant size: consumers who come back within 1 hour and click on the same film as before, for instance, are 3.7 p.p. more likely to select tickets in *Shrouded* than in *Inclusive*.

Table C.3. *Lower-bound estimation of ticket selection for the second initiated purchase.*

Parameter	**Within 1 hour**			**At least 1 hour**		
	All	Same	Other	All	Same	Other
Shrouded	0.040***	0.037***	0.085	0.069***	0.035*	0.051***
	(0.011)	(0.012)	(0.063)	(0.013)	(0.021)	(0.018)
Movie FE	yes	yes	no	yes	yes	yes
Time FE	yes	yes	no	yes	yes	yes
2D Substitute	yes	yes	no	yes	yes	yes
# Observations	7,520	7,293	212	5,608	3,627	4,760

Notes to Table C.3: *The table presents the results of a worst-case scenario for the shrouding effect. The dependent variable of the OLS-regressions is a binary indicator of whether a consumer selected tickets for the second initiated purchase for a 3D movie. The independent variable of interest is a treatment indicator for Shrouded. We add the* *same controls as in the main text, except for the subsample "within 1 hour, other film" with only few observations. Standard errors are provided in parentheses. *: Significant at 10%. ***: Significant at 1%.*

Purchases. When looking at the probability to buy tickets (at some point in time) for the second 3D show that a consumer has clicked on during the treatment period, we again do not observe any significant treatment effects. This suggests, in particular, that the still significant effect of shrouding on the likelihood of selecting tickets, conditional on the second initiated purchase process, is not driven by consumers who initially balked at the high surcharge on their first visit, but then decided that the surcharge is acceptable and thus came back to buy tickets.

Table C.4. *Treatment effects on purchases for the second initiated purchase process.*

Parameter	**Within 1 hour**			**At least 1 hour**		
	All	Same	Other	All	Same	Other
Partitioned	0.015	0.016	-0.039	-0.000	0.017	-0.016
	(0.011)	(0.011)	(0.062)	(0.013)	(0.020)	(0.017)
Shrouded	0.011	0.010	0.012	-0.006	-0.011	-0.005
	(0.011)	(0.011)	(0.063)	(0.013)	(0.020)	(0.017)
Movie FE	yes	yes	no	yes	yes	yes
Time FE	yes	yes	no	yes	yes	yes
2D Substitute	yes	yes	no	yes	yes	yes
# Observations	11,516	11,186	330	8,387	3,627	4,760

Notes to Table C.4: *The table presents the results of OLS-regressions. The dependent variable is a binary indicator of whether a consumer buys, at some point in time, tickets for the second 3D show that a consumer has clicked on during the intervention period. The independent variables of interest are treatment indicators (whereby Inclusive serves as the base category). We add the same controls as in the main text, except for the subsample "within 1 hour, other film" with only few observations. Standard errors are provided in parentheses.*

Appendix D: Decision Screens in the Different Treatments

Figure D.1. *Cinema schedule in the online shop (prior to the log-in).*

Notes to Figure D.1: *Before clicking on a given show (i.e., a combination of date and time) of Solo: A Star Wars Story and logging-in with an email address and a password, the consumer does not obtain any price information.*

Figure D.2. *Price presentation on the initial screen in Inclusive.*

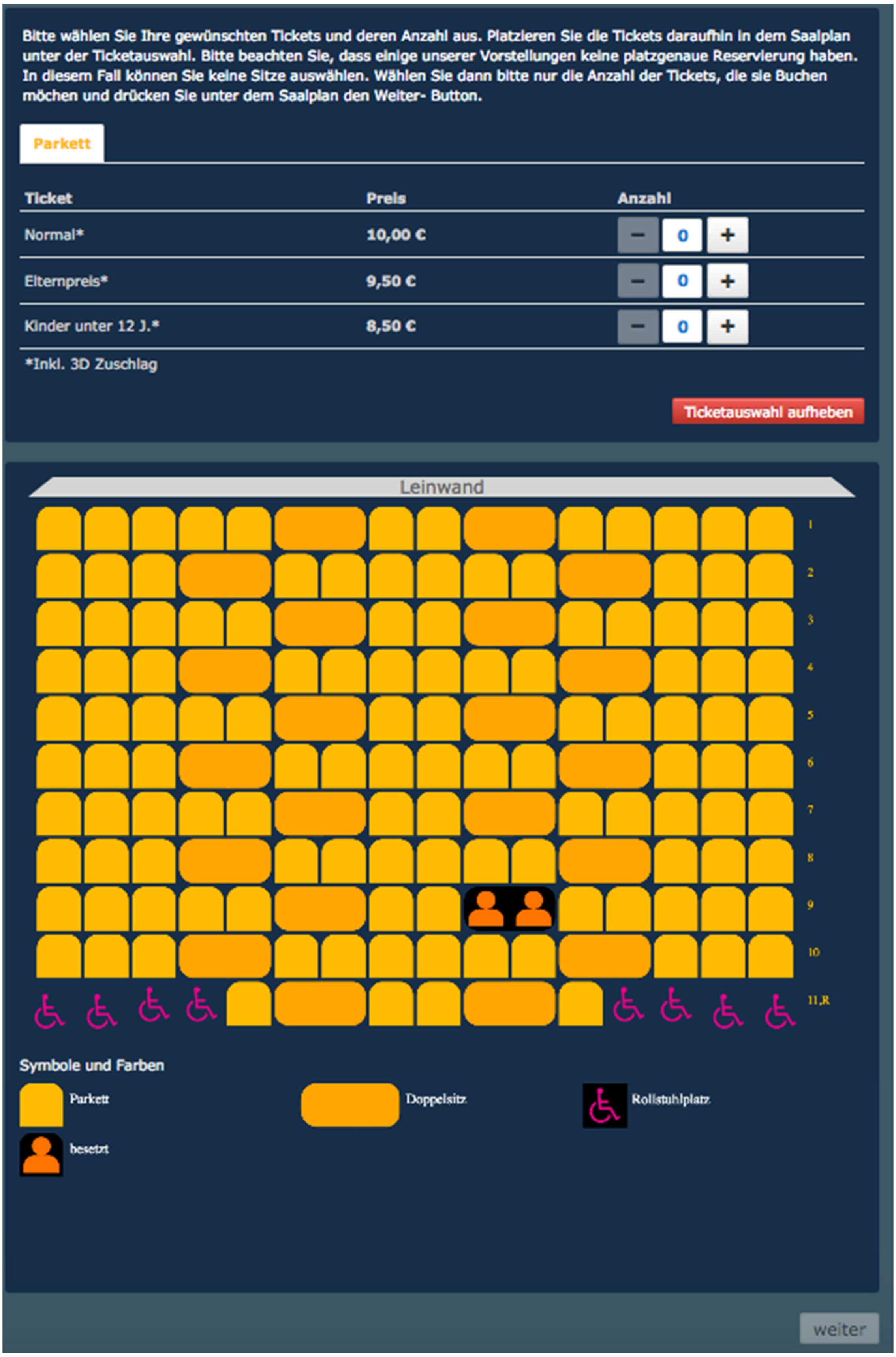

Figure D.3. *Price presentation on the initial screen in Partitioned.*

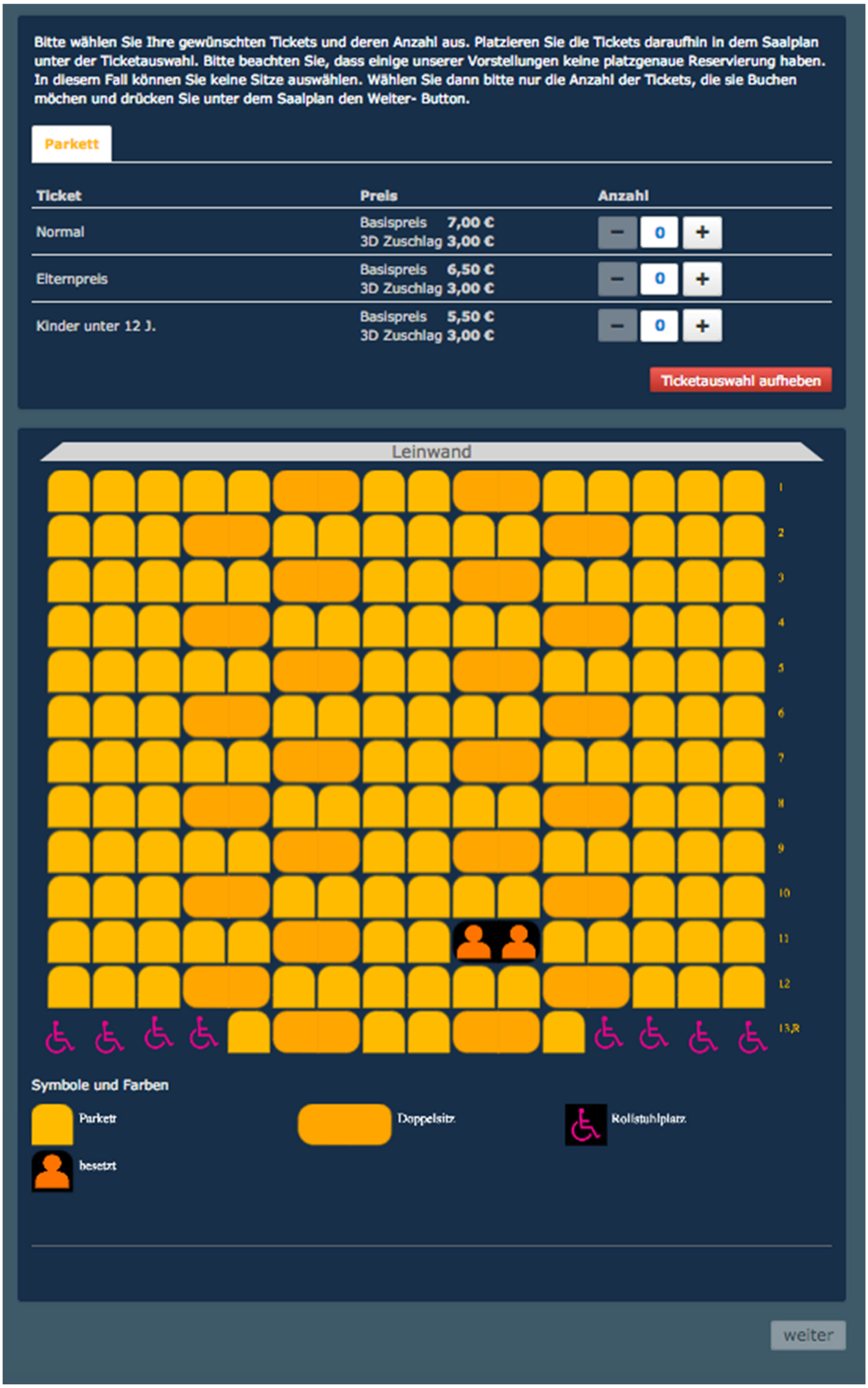

Figure D.4. *Price presentation on the initial screen in Exclusive.*